The Design of Resilient Engineering Infrastructure Systems

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To my lovely family

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification at the University of Cambridge, or any other university. Unless stated in the text, this dissertation is my own work and does not include the outcome of work done in collaboration. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Some of the work contained in this dissertation has been published and presented as below:

1. **Mak, W.H.J.**, and Clarkson, P.J., (2017). Towards the Design of Resilient Large-Scale Engineering Systems. In *Procedia CIRP*, 60, pp.536-541. https://doi.org/10.1016/j.procir.2017.01.034

2. **Mak, J.**, Cassidy, S. and Clarkson, P.J., (2017). Towards an Assessment of Resilience in Telecom Infrastructure Projects using Real Options. In *Proceedings of the 21st International Conference on Engineering Design (ICED 17)*, Vancouver, Canada, 21-25 Aug, 2017

3. **Mak, W.H.J.**, Cardin, M.A., Liu, Z., Clarkson, P.J., (2018). Towards the Design of Resilient Waste-to-Energy Systems Using Bayesian Networks. In *ASME International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, Quebec City, Canada 26-29 Aug, 2018

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Abstract

The concept of resilience has emerged from a number of domains to address how systems, people as well as organisations can handle uncertainty and thereby not only survive hardship, but also thrive and prosper. This is of particular importance for engineering infrastructure systems which, due to the inherently long lifecycles giving rise to many unknowns, need to be designed for resilience such that it not only maintains operations in the face of day-to-day demands, but also continue to be able to evolve for the future. While there has been substantial interest in resilience from both academia and industry, exactly how such systems may be endowed with resilience to address these concerns from an engineering design perspective is less clear.

To this end, a literature review was first conducted to compile the definitions and characteristics of resilience across the domains of engineering, organisational management and ecology. The characteristics were found to comprise: absorbing disturbances, adapting for change and thriving for the future. These were then mapped to the engineering design ilities of robustness, adaptability and flexibility before being brought together in a conceptual model to form a strategic view for resilience. Further methods from resilience and engineering design literature were then consulted to understand how this particular view could be modelled and evaluated. This led to the development of a preliminary model using the Least Squares Monte Carlo method adapted for a telecommunications case study.

The insights gained from these explorations were then used to drive the synthesis of a novel support method whereby the design for flexibility framework was adapted to include decision modelling with Bayesian Networks and for resilience analysis. Here, resilience is taken to be the maximisation of the system economic lifecycle value under uncertainty, as measured by Expected Net Present Value, through robust and flexible strategies. This was applied to two case studies involving infrastructure systems: the first built upon existing work based on a Waste-to-Energy system in Singapore to verify the new method while the second applied the support method with BT, a multinational telecommunications company based in the UK, to gauge reception of this approach in industry. In

both cases, the initial capacity and maximum number of upgrades served as proxies for robustness and flexibility respectively. Results demonstrate that Bayesian Networks are able to model decision rules for flexibility by selecting technology options over time given observations on the system and are also useful for extracting expert domain knowledge. While the construction of Bayesian Networks are subjective, they present an intuitive visualisation of the dependencies in a system and as such, engaged stakeholder interest. Resilience analysis examined the effect of volatility and drift of demand on the design strategies and indeed, there existed a trade-off between robust and flexible strategies. Furthermore, the greater utility of the support method lies in aiding decision makers in exploring the solution space and prompting discussions for what-if scenarios for the organisation.

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Chapter 1

Introduction

1.1 Motivation

The present world is changing all the time — and with ever increasing speed, complexity and uncertainty. How a system responds to change, both from within the system and from the environment, can mean the difference between success and failure.

This work aims to address, from an engineering systems design perspective, how a system may be designed to embrace change and how this should be managed. To this end, the effect of uncertainty on the system must be better understood and the tipping point where the *system* itself has to transform to accommodate change is examined. And indeed, how can a system be designed to not just *survive* challenging times but also *thrive* in a world of uncertainty moving forward? What is certain, however, is that there will be more change to come. By investigating and understanding these challenges, it is hoped that this work can aid in designing systems that are better prepared for the future.

These challenges have recently been associated with "resilience" in both academia and industry. In the traditional sense, resilience can describe the concept of recovery following some negative change, disturbance or adversity so that organisations continue to operate business as usual, individuals recover from trauma and engineering systems behave as designed. For example, on March 17$^{\text{th}}$ 2000, lightning struck one of Philips' semiconductor manufacturing plants and started a fire. The fire itself was extinguished quickly, but more interestingly, however, was the chain of events that followed. Although a small fire, the smoke contaminated clean rooms making the plant inoperable for weeks and ruined semiconductor chips that were to go on to create millions of mobile phones. Philips proceeded to inform their customers which included the then major mobile producers Nokia and LM Ericsson AB. What was interesting was the response of the two companies. Nokia sent engineers to the Philips plant to assess the damage and, upon learning that catching up on production could take months, brought together a team to tackle the problem and find alternate suppliers. Furthermore, meetings were held at the highest level with the chief executives of both companies working together and stating that, “The goal was simple: For a little period, Philips and Nokia would operate as one company regarding these components”. On the other hand, Ericsson had a very different response following the initial contact from Philips. The problem was not escalated to senior management, treated as a minor glitch and Ericsson decided to wait, using their own backup supplies. By the time Ericsson did respond, Nokia had already taken any of the market’s spare capacity and, without alternative suppliers, Ericsson failed to obtain necessary components. The result was that Ericsson reported a US$430 to US$570 million loss in that quarter while Nokia continued to roll out their next generation of phones and subsequently increased their market share by 3% (Sheffi, 2005; Starr *et al.*, 2003). The actions of the two companies gave significantly different outcomes and illustrates the need for appropriate measures as well as responses to overcome threats to an organisation.

From this anecdote, it is clear that the ability to adapt is crucial in allowing the system to recover. That is, when reserve supplies or redundancies are exhausted, the system should change protocol – in this case, Nokia switched supplier. This prompts the question of how much redundancy should a system require? And at what point should decision makers choose to switch suppliers instead of relying on existing reserves? Popular lean methodologies suggest that systems should reduce waste in order to improve quality, reduce production times and lower cost (Krafcik, 1988). Yet by having a small reserve supply, the system could become vulnerable to swings in uncertainty (Christopher & Peck, 2004). From an engineering design and change management perspective, it is therefore important to understand how much redundancy a system requires, or how *robust* to make the system, and simultaneously understand how to allow the system to *adapt* once these limits are breached. This, however, is only one facet of resilience.

The traditional view of resilience has been typically associated with negative connotations, similar to the previous case, but there is now growing recognition that resilience should not just be about the negative, but should also encompass positive changes: to change for new opportunities. Even in times of uncertainty, organisations do not want to just endure turbulence, but also excel and prosper despite the challenges. In resilience literature this has been recognised through the necessity to not just survive but *thrive* (Hamel & Välikangas, 2003; Pal, 2013). It is thus important that uncertainty should not just be a synonym for risk, but also incorporate the other “tail of the distribution” where it should also include the ability to change as well as adapt for new opportunities (de Neufville *et al.*, 2004). Thus there is a view that resilience is not just about surviving at the operational, day-to-day level, but also at the strategic level to ensure long-term success.

In order to take advantage of these new opportunities, a system needs be designed to be *flexible* so that it can exploit opportunity when it comes. One such example is the Ponte 25 de Abril suspension bridge over the Tagus River in Lisbon, Portugal. Originally built with a single deck for road traffic, it was designed so that it had the strength to accommodate a secondary railroad deck in the future (Figure 1.1). Although adding a second deck involved a substantial retrofit, the planners only exercised this option when there was enough demand stimulated by the single deck bridge (Gessner & Jardim, 1998). Essentially, the designers anticipated that the capacity of the bridge could grow which led to mechanisms being designed into the bridge so that capacity could be expanded when appropriate and thus managing both risk and opportunity.

It is therefore argued here that by designing systems to be resilient, they are better equipped through robust, adaptable and flexible mechanisms to both weather hardship and succeed in the future. This thesis therefore explores how the lens of resilience may be used to allow decision makers better design engineering systems and thereby invest in future technologies to protect against but also succeed in light of forthcoming uncertainties.

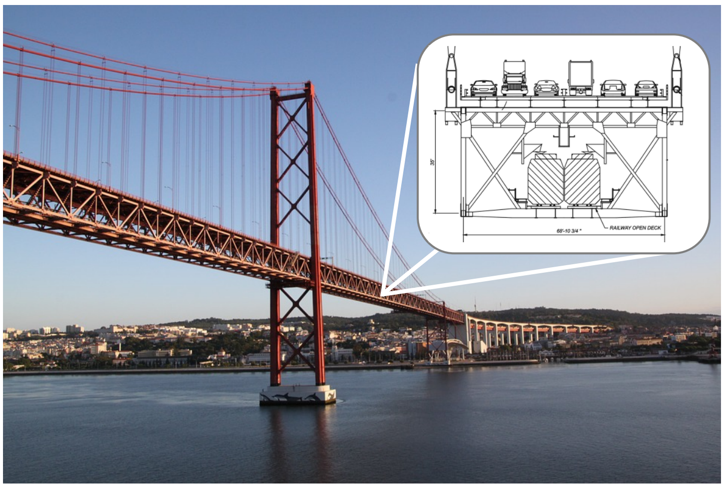


Figure 1.1. Ponte 25 de Abril Suspension bridge with cross section showing upper road deck and lower railway deck

1.2 Designing Resilience into Engineering Infrastructure Systems

While resilience has found relevance in numerous disciplines, it is of particular importance to engineering infrastructure systems such as telecommunications, power and transport networks to ensure the stable functioning of society. Here, infrastructure systems are defined as:

> *"facilities, systems, sites, information, people, networks and processes necessary for a country to function and upon which daily life depends"*
>
> — Cabinet Office UK (2010)

Failure in these services can bring major disruption to a community and recovery can incur substantial time and cost (Comfort *et al.*, 2010). For example, in 2005 Hurricane Katrina flooded approximately 80% of the city of New Orleans causing widespread disruption to the population and municipal services (Colten *et al.*, 2008). Although it was not the strongest hurricane on record, its landfall location on the Gulf Coast made it the most devastating and costliest disasters in US history costing US$3.4 billion in insurance claims alone (Hudson *et al.*, 2012). Other natural disasters such as earthquakes, tsunamis and floods have also led to significant impact and cost to infrastructures across the world (Neate, 2012). However, it is not only failure in such systems that incurs substantial costs. The upfront cost of investment due to the large scale and complexity of infrastructure networks is also considerable. For example, the UK 2017 public and private infrastructure pipeline set out over £600 billion of planned investment over the subsequent 10 years (Infrastructure and Projects Authority UK, 2017).

Research into the design of infrastructure systems are therefore of academic and industrial value since failure and remedial action will take extensive time, rework and re-investment (Love & Li, 2000). From an engineering design perspective, infrastructure systems characteristically have relatively long life cycles which thus expose these systems to uncertainties through a range of time-scales: from uncertainty in immediate, day-to-day operations to strategic unknowns in the far future (de Neufville *et al.*, 2004). Infrastructure systems, which touch many areas of peoples' daily lives, therefore need to be resilient, not only to withstand imminent shocks such as natural disasters and demand fluctuations, but also for the long-term in order to maintain the proper functioning and prosperity of communities.

Exactly how a system is endowed with such properties is less well defined. This work aims to address this by assessing design strategies that can instil resilience into infrastructure systems from an engineering design perspective. While the scientific method is concerned with the analysis of the natural world, engineering design may be seen to be focused on synthesis and building "how [things] ought to be in order to attain goals" (Simon, 1969). In this case, how ought the infrastructure system be designed to become resilient? Thus, while the scientific perspective may ask what makes a system resilient, from the engineering design point of view, the question becomes, "how can we become resilient?" Both of these approaches are necessary in this work to not just understand the core concept of resilience, but also investigate how it can be designed into a system and improve response to uncertainty. The engineering design process also differs by being an iterative process where there is more emphasis on developing creative and innovative solutions that satisfy product requirements set by technological, economic, legal, environmental and human related constraints in order to create a useful end product (Pahl & Beitz, 2013). This wider view of the system is important as infrastructure projects form the technological backbones of society and therefore commercial and social implications should also be studied. Overall success therefore may not result solely from technological brilliance but softer factors from the market should also be considered as sources of uncertainty (de Neufville, 2003). In the example of Nokia and LM Ericsson, the crises resulted, not from the product, but from problems in the supply chain and the organisation. de Weck *et al.* (2004) also illustrates a similar point in a study of the Iridium communication satellites with the conclusion that, while the satellite technology itself was technically sound, the reliance on an inaccurate demand projection led the company to a loss of USD$5 billion and ultimately bankruptcy. In designing infrastructure systems, this holistic systems approach is beneficial in understanding how the system, as a whole, interacts. This broader understanding of the system can therefore aid decision makers in the organisation assess the long and short-term impacts of management decisions and assess whether improvements are necessary (Hollnagel *et al.*, 2006).

Given these initial motivations, the remainder of this chapter serves to introduce the research methodology which incorporates these principles of engineering design into this work as well as define the research questions for investigation.

1.3 Research Methodology

The need for resilience in engineering infrastructure systems and the merits of an engineering design approach have been highlighted in the previous sections. To guide further work, an appropriate design methodology should be chosen to maximise the success of this project. There exists several methodologies in literature to structure scientific investigation. In the field of engineering design, there has been work done by Antonsson (1987), advocating a six-step process consisting of 1) propose/hypothesise that a set of rules for design can elucidate part of the design process 2) develop those rules 3) have novice designers learn and apply the rules 4) measure their design productivity 5) evaluate the results to confirm or refute the hypothesis and 6) evaluate the hypothesis. The main aim of this approach was to generate more scientifically rigorous hypotheses for design research which could be tested. The Eightfold Path was proposed by Eckert *et al.* (2003) to give structure to design research and is especially suited for larger research projects with multiple case studies. Another methodology by Duffy & Donnell (1998) presents an approach which includes the steps of understanding the design problem, generating a hypothesis which is then formulated into a research problem, developing a solution, evaluation and documentation.

One of the most successful in engineering design, and the methodology adopted by this thesis, is the Design Research Methodology (DRM) by Blessing & Chakrabarti (2009). The DRM gives clear guidance specifically for PhD projects and standalone projects to produce well-rounded results. The methodology comprises a detailed iterative process for different stages of design research as shown in Figure 1.2.

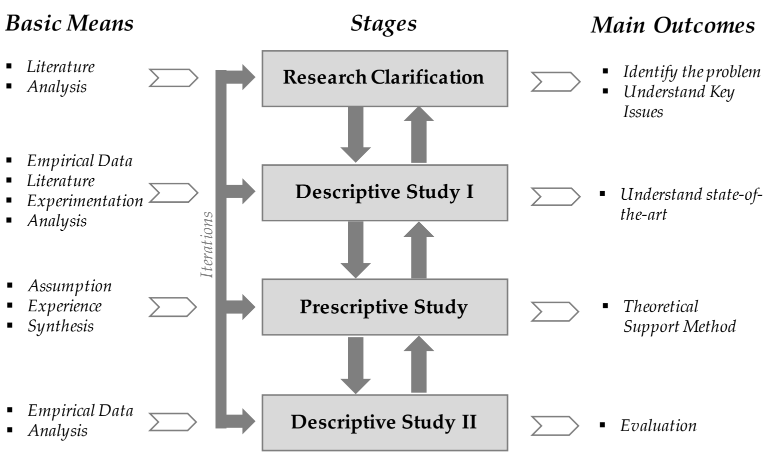


Figure 1.2. The Design Research Methodology

In particular, the DRM integrates two main aspects for design research: the development of both understanding and support. This is essential for this work since both the definitions of what makes a system resilient as well as how the system may be designed to be resilient need to be investigated. Specifically, Research Clarification phase establishes research direction by formulating the hypothesis, requirements and research questions to be addressed by identifying the key challenges both in academia and in industry. A deeper understanding of the state-of-the-art is developed in the Descriptive Study I and usually involves an extended literature review to identify research gaps. A support method is then developed in the Prescriptive Study which addresses and improves upon the challenges defined in Descriptive Study I. The proposed support method is then applied and evaluated in Descriptive Study II to assess the usefulness and applicability of the method. A summary of the DRM applied in this work is given in Figure 1.3 with further particulars presented in Chapter 3.

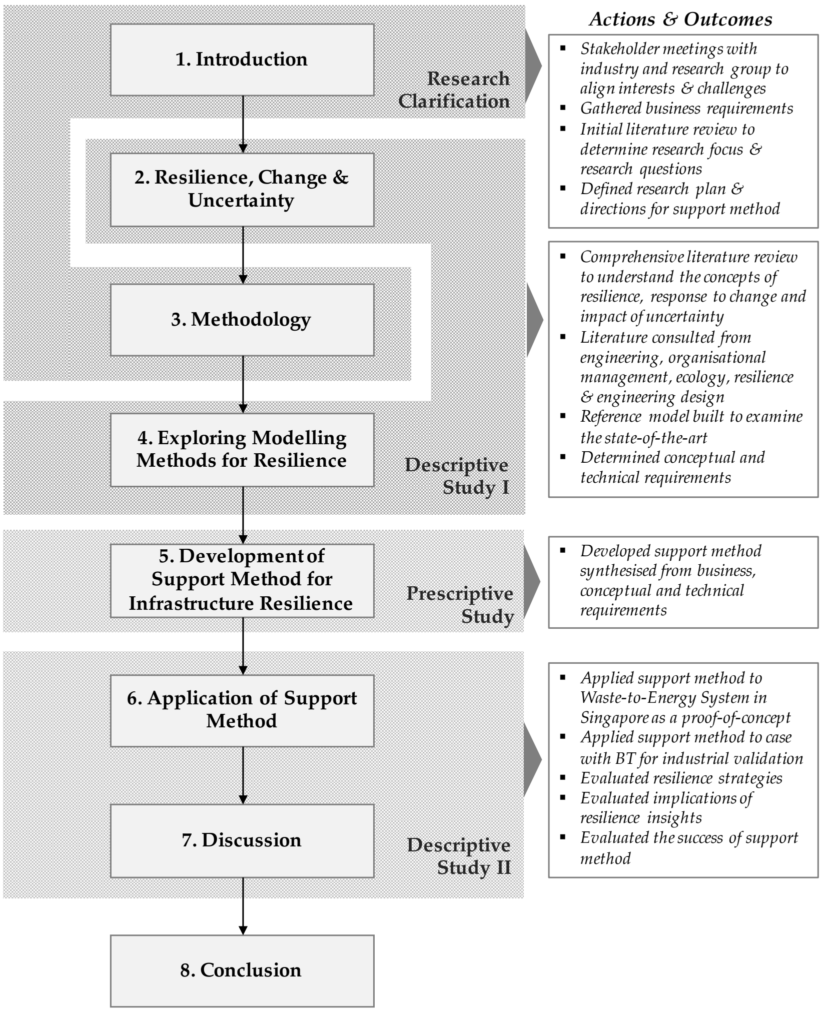


Figure 1.3. The DRM applied to this thesis

1.4 Research Hypothesis and Research Questions

In accordance with the DRM, the Research Clarification phase in this work involved initial research into engineering design and resilience to define the research direction. These were complemented with discussions with the industrial sponsor, BT Group plc, hereafter BT, to identify practical challenges that industry currently face. A number of iterations and meetings were necessary to ensure that all stakeholders — industrial sponsor, academic group and author — align expectations and relevant research questions are produced.

BT is a world leading telecommunications provider and delivers critical infrastructure for the UK and across the world. A key aspect of their business growth pertains to understanding how to invest in their fibre optics infrastructure. Different characteristics of cities, say London with relatively higher population density and thus larger bandwidth requirements compared to Cambridge, lead to particular investment strategies and requirements for each area. In addition to these operational constraints, excavating land to deploy and repair such cables is costly and therefore a strategic view of infrastructure upgrades is necessary so that land does not have to be dug up repeatedly. In terms of resilience, this infrastructure should be designed to be robust enough to meet operational demands such as fluctuating bandwidth requirements for each area, yet also be flexible so that the infrastructure can be upgraded cost-efficiently and evolved for new opportunities.

The business requirements were therefore to understand what and when fibre optics infrastructure technologies options should be changed as specified in the list below:

Business Requirements

- To understand what technology options are most appropriate for different areas of Cambridgeshire
- To understand when technology options should be changed for different areas of Cambridgeshire
- To understand the optimal order of change for each of the technologies options for different areas of Cambridgeshire

These requirements, along with conceptual and technical requirements derived through the literature review (Chapter 2) and preliminary model (Chapter 4) respectively drives the synthesis of the support model (Chapter 5).

With these initial motivations, requirements and research, the hypothesis for this work was formulated as below:

> **Hypothesis**
> Designing resilience into engineering infrastructure systems through engineering design strategies, allow such systems to better accommodate forthcoming uncertainties.

This hypothesis is tested through six more specific research questions (RQs). The first RQ examines the current understanding of resilience and must be explored to establish a more concrete definition of resilience in engineering infrastructure systems for this work moving forward (RQ1). This is especially important due to the wide ranging use of the term and overlapping definitions that exist between domains. Similarly, the engineering properties of what makes a system resilient must be distilled and following this, how these properties can be designed into the system need to be investigated (RQ2). This first set of questions (Table 1.1) are part of the Descriptive Study I phase of the DRM and lead to a conceptual model which amalgamates these findings. These also give conceptual requirements for the support method and are presented in Chapter 2.

Table 1.1. Research Questions: Understanding Resilience in Engineering Infrastructure Systems

Understanding Resilience in Engineering Infrastructure Systems	
RQ1	What is a useful definition of resilience for engineering infrastructure systems?
RQ2	What engineering design properties are required by engineering infrastructure systems to enable resilience?

With this understanding of the state-of-the-art in resilience and engineering infrastructure systems from these initial two questions, Chapter 3 discusses directions for the synthesis of the novel support method. Specifically, in order to assess the impact of new infrastructure designs and whether there has been any improvement in the system's resilience, methods to model and evaluate resilience need to be also studied (RQ3). Chapter 4 presents a preliminary model to examine the technical limitations of the current models of resilience, leading to technical requirements, and Chapter 5 describes the novel support method for Prescriptive Study in this work. Upon establishing the support method, questions regarding how an engineering infrastructure system may be designed to be resilient can then be examined (RQ4) by applying the support method on case studies as detailed in Chapter 6. These questions regarding the modelling of resilience in engineering infrastructure systems are given in Table 1.2.

Table 1.2. Research Questions: Modelling Resilience in Engineering Infrastructure Systems

Modelling Resilience in Engineering Infrastructure Systems	
RQ3	How can resilience in engineering infrastructure systems be modelled?
RQ4	How can engineering design strategies be used to achieve resilience in engineering infrastructure systems?

The final two research questions takes a step back to verify the model against the business, conceptual and technical requirements (RQ5) as well as understand the usefulness and limitations of this work (RQ6). These are presented below in Table 1.3 and further discussed in Chapter 7.

Table 1.3. Research Questions: Achieving Resilience in Engineering Infrastructure Systems

Achieving Resilience in Engineering Infrastructure Systems	
RQ5	How well does the support method meet requirements for designing resilient engineering infrastructure systems?
RQ6	How fit for purpose is the support method in designing resilient engineering infrastructure systems?

1.5 Structure of Thesis

This thesis is presented in eight chapters and is structured following the DRM as summarised below:

1. **Introduction:** The main research motivations, hypothesis, research questions, and the theme of resilience in engineering infrastructure systems is introduced.
2. **Resilience, Change & Uncertainty:** Literature is examined from the fields of resilience and engineering design to give an overview of extant research and establish conceptual requirements for work moving forwards.
3. **Methodology:** The first set of research questions are revisited to understand the research gap in the literature and opportunities for further work.
4. **Exploring Methods for Resilience:** The literature survey prompted to the need for quantitative methods for assessing resilience. A preliminary model using the real options paradigm is adapted for resilience. The limitations of this model serve as technical requirements for a novel support method.
5. **Support Method for Infrastructure Resilience:** Based on the requirements of the literature review, preliminary model and industry discussions, a novel support method is developed to evaluate resilience and the design strategies to embed resilience.
6. **Application of Support Method:** The utility of the support method is demonstrated through two case studies: a theoretical proof-of-concept with Waste-to-Energy systems in Singapore and with telecommunications case in BT to evaluate the support method in practice.
7. **Discussion:** Review of the main findings, contributions, validation and success of the support method both from an academic and industrial perspective.
8. **Conclusion:** Revisits the research questions and evaluates whether the research outcomes have addressed the questions appropriately. The major contributions of this work are summarised and presented.

Chapter 2

Resilience, Change & Uncertainty

Before being able to design resilient engineering infrastructure systems, requirements must first be established to gain an understanding of what exactly needs to be designed. This further allows for validation of the work by setting criteria against which to assess the suitability of the final support method and the contribution for this work. This section thus explores the conceptual requirements of resilience through a literature review in a number of domains to build a concrete definition of the term with which to move forward and is particularly important due to the wide ranging use of resilience and the overlapping definitions that exists. With these requirements, the concepts and methods for resilience are then related to engineering design approaches to hypothesise how resilience may be designed into a system. This leads to the first contribution of this work – a conceptual model of resilience for infrastructure systems. It is then further necessary to understand how resilience can be measured and evaluated so that the designs can be improved and the performance of the system may be bettered. This chapter then closes with the identified research gaps for further work and points towards methods from engineering design which warrant further review in order to satisfy these requirements.

2.1 Characterising Resilience

Resilience has traditionally been associated with negative connotations: the ability to recover from adversity or trauma. Indeed, a definition from the Oxford English Dictionary gives:

> *"The quality or fact of being able to recover quickly or easily from, or resist being affected by, a misfortune, shock, illness, etc.; robustness; adaptability."*
>
> — OED Online (2018)

While this is similar in other dictionaries (Collins English Dictionary, 2018; Merriam-Webster, 2018) there is less consensus across domains in academia and in industry. The term "resilience" was popularised by Holling in 1973 within the field of ecology to assess the stability and resilience of interacting populations with respect to environmental pressures. In their work, resilience is defined as the "persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist" (Holling, 1973). This concept of a system's interaction with the environment and surviving disturbances forms the foundations for resilience in many other fields including supply chain management (Sheffi & Rice Jr., 2005), network design (Sterbenz *et al.*, 2011), crisis management (McManus, 2008), psychology (Rutter, 1987), power grids (Liu *et al.*, 2016), road networks (Gauthier *et al.*, 2018) and resilience engineering (Hollnagel *et al.*, 2006). Indeed, the number of scientific articles containing the keyword "resilience" grew more than ten-fold from 1995-2011 (Longstaff *et al.*, 2013). This popularity has led to the evolution of domain-specific definitions and methods through which to achieve resilience.

The remainder of this subsection thus serves to explore the application of resilience in these various domains and to establish direction for this thesis. Since there has been substantial research conducted in these fields, the first part of the literature search is delimited to work with the keyword "resilience" from engineering research and also ecological literature where there have been significant complementary views of resilience. Moreover, infrastructure systems inherently involve many stakeholders and there has been recognition that risks arise not only from technology, but also from the organisation. This leads to the intertwining of the fields of engineering and management which gives reason for including organisational resilience in the literature search. The second part of the literature review studied how these properties could then be built into the system from an engineering design and engineering change management perspective. These were chosen as these fields cover methods to manage change propagation through an engineering system making them potential areas to consider for resilience assessment. This is summarised in Table 2.1.

Table 2.1. Research Scope for this thesis

Research Scope	
Research Focus	Design of Resilience Engineering Infrastructure Systems
Resilience literature to be consulted	*Resilience in:* Engineering (including infrastructure systems), Operations, Management, Ecology
Engineering Design literature to be consulted	Engineering Design, Engineering Change Management

A multitude of definitions for resilience have been uncovered from these fields and some papers that give explicit definitions for resilience are presented in Table 2.2. These are sorted chronologically by discipline. While differing in application, there seems to be three main concepts that have emerged from the different disciplines. These are included in the table with check-marks indicating that a paper discussed a particular concept. It was found that a system, whether it be technical, human, or otherwise, must be able to withstand disturbances. This was found unanimously across resilience literature. How this is achieved, however, varies between domains. First, a system can simply *absorb disturbances* without the need to react to external stimulation or disturbance and there is sufficient buffer or redundancy in the system to cope. Second, a system can *adapt to change* through some reorganisation of resources or feedback loops and involves some change within the system to recover back to normal. The third concept involves some evolution of the system such that it can perform for new conditions or requirements and thereby *thrive for the future.*

These three concepts are first discussed in this subsection before relating these characteristics to design strategies through which to achieve resilience in the next subsection. Following this, a conceptual model is established which unifies these perspectives in the context of engineering design and forms the first contribution of this work.

Table 2.2. Definitions of Resilience

Authors	Year	Discipline	Definition	Absorbing Disturbances	Adapting for Change	Thriving for the Future
OED Online	2018	-	The quality or fact of being able to recover quickly or easily from, or resist being affected by, a shock, illness, etc.; robustness; adaptability.	✓	✓	
Dinh *et al.*	2012	Engineering (process)	The ability to recover quickly after an upset.	✓		
Jackson & Ferris	2013	Engineering (systems)	The potential for contributing to the avoidance, survival, or recovery of a system that has encountered a threat.	✓	✓	
Neches & Madni	2013	Engineering (systems)	The ability of a system to adapt affordably and perform effectively across a wide range of operational contexts, where context is defined by mission, environment, threat, and force disposition.	✓	✓	
Liu *et al.*	2017	Engineering (power grids)	The survivability of power systems when experiencing extreme events.	✓		
Gauthier *et al.*	2018	Engineering (road networks)	The ability of a network to absorb and react to adverse events.	✓		
Vidal *et al.*	2009	Engineering (nuclear/ sociotechnical)	The capacity of organizational systems to function adequately under environment variations.	✓	✓	
Furniss *et al.*	2011	Engineering (nuclear/ sociotechnical)	The ability to recover from some unexpected event, or to avoid accidents happening despite the persistence of poor circumstances.	✓	✓	
Dalziell & McManus	2004	Resilience Engineering (sociotechnical)	The overarching goal of a system to continue to function to the fullest possible extent in the face of stress to achieve its purpose, where resilience is a function of both the vulnerability of the system and its adaptive capacity.	✓	✓	✓
Wears *et al.*	2006	Resilience Engineering (sociotechnical)	To facilitate future functionality in anticipation of returning to normal operations.	✓	✓	
Sundström & Hollnagel	2006	Resilience Engineering (sociotechnical)	The organisation's ability to successfully adjust to the compounded impact of internal and external events over a significant time period.	✓	✓	
Hollnagel *et al.*	2007	Resilience Engineering (sociotechnical)	The ability of systems to anticipate and adapt to the potenial for surprise and failure.	✓	✓	
Longstaff *et al.*	2013	Resilience Engineering (sociotechnical)	In engineering: The capacity to rebound and recover; In business, psychology, social studies: The capability to maintain a desirable state; In ecology: The capacity of the systems to withstand stress; In social systems: The capability to adapt and thrive.	✓	✓	✓
Pflanz & Levis	2012	Computer Science	[The ability] to survive and recover from disruption.	✓		

Wódczak	2011	Autonomics	[The ability to] automatically adjust the way the mobile network is reorganising its deployment to best fit the quality of service expected by the end users.		✓	
Vlacheas *et al.*	2013	Autonomics	[The] persistence of dependability when facing changes.		✓	
Arghandeh *et al.*	2016	Cyber-physical Systems	The ability to recognize, adapt to, and absorb disturbances in a timely manner.	✓	✓	
Sheffi	2005	Supply chain	The ability to bounce back from disruptions and disaster by building in redundancy and flexibility.	✓		✓
Sterbenz *et al.*	2011	Networks	The ability of the network to provide desired service even when challenged by attacks, large-scale disasters, and other failures.	✓	✓	
Hamel & Välikangas	2003	Organisational Behaviour	The ability to dynamically reinvent business models and strategies as circumstances change, to continuously anticipate and adjust to changes that threaten their core earning power - and to change before the need becomes desperately obvious.	✓	✓	✓
Christopher & Rutherford	2004	Organisational Behaviour	The ability of a system to return to its original (or desired) state after being disturbed.	✓	✓	
McManus	2008	Organisational Behaviour	A function of the overall situation awareness, keystone vulnerabilities and adaptive capacity of an organisation in a complex, dynamic and interrelated environment.		✓	
Gibson & Tarrant	2010	Organisational Behaviour	Resilience is not just about "bouncing back from adversity" but is more broadly concerned with adaptive capacity and how we better understand and address uncertainty in our internal and external environments.	✓	✓	✓
Limnios & Mazzarol	2011	Organisational Behaviour	The magnitude of disturbance the system can tolerate and still persist.	✓	✓	
Weick *et al.*	2008	Organisational Behaviour	[The] capacity to cope with unanticipated dangers after they have become manifest, learning to bounce back.	✓	✓	
Holling	1973	Ecology	The persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist.	✓		✓
Carpenter *et al.*	2001	Ecology	The magnitude of disturbance that can be tolerated before a socioecological system (SES) moves to a different region of state space controlled by a different set of processes.	✓	✓	✓
Fiksel	2003	Ecology	The ability to resist disorder; Through adaptation and evolution, it is capable of surviving large perturbations.	✓	✓	✓
Walker *et al.*	2004	Ecology	Ecological Resilience: the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks. Engineering resilience: The notion of speed of return to equilibrium.	✓	✓	✓
Derissen *et al.*	2011	Ecology	A system may flip from one domain of attraction into another one as a result of exogenous disturbance. If the system will not flip due to exogenous disturbance, the system in its initial state is called resilient.	✓		✓

2.1.1 Absorbing Disturbances

While the concept of resilience notably began in ecology, resilience in engineering gained attention largely from Hollnagel's work following the 1st Resilience Engineering Symposium. Work in this research area focuses on safety, mitigating risk and the analysis of accidents and is applied through case studies in high risk industries such as nuclear plants (Carvalho *et al.*, 2008; Vidal *et al.*, 2009), offshore helicopter transport (Gomes *et al.*, 2009), the Columbia Space Shuttle disaster (Woods, 2003) and emergency departments (Wears *et al.*, 2006). Much of this work has stemmed from reliability theory and designing High Reliability Organisations (HRO) which aims to reduce failure through highly standardised routines. As such, much of the analysis traditionally revolves around identifying vulnerabilities, risk analysis and calculating the probability of failure. In such an analysis, the focus is on calculating the likelihood of an event, typically a disturbance or failure occurring. Different types of risk can be visualised through a risk matrix as shown in Figure 2.1, adapted from Hollnagel (2011).

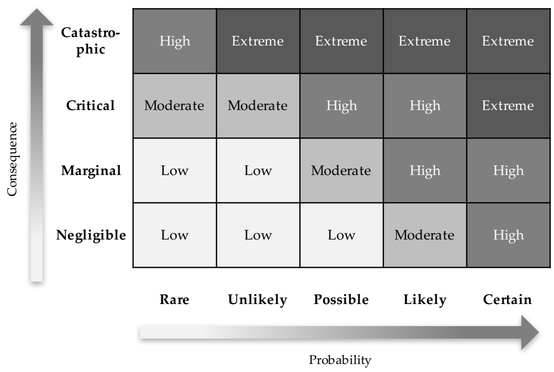


Figure 2.1. Traditional risk matrix

Resilience, however, then evolved from the acknowledgement that it is difficult, if not impossible to account for all possible failures of a system. Instead of analysing the endless possibilities of how it could go wrong, resilience thus adopted a more proactive approach of understanding how the system should respond to unanticipated issues (Dalziell & McManus, 2004; Madni & Jackson, 2009; Woods, 2006). Resilience thus became more concerned with the uncertainties, or "unknown unknowns", with unknown probability estimates and how the system responds to disturbance. The common view of resilience in engineering is to respond by "bouncing back" and recovering to the previous, normal state (Pflanz & Levis, 2012; Righi *et al.*, 2015; Weick *et al.*, 2008). A system can be further thought of being in one of three states: normal, upset and catastrophic as shown in Figure 2.2 (Dinh *et al.*, 2012).

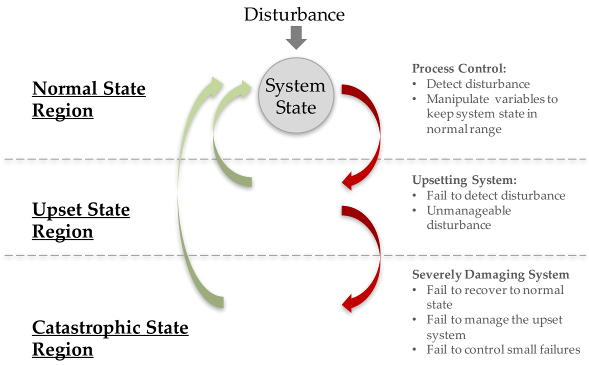


Figure 2.2. System states upon disturbance, adapted from Dinh *et al.* (2012)

The normal state handles a certain amount of uncertainty by detecting disturbances and manipulating processes to maintain normal operating conditions. In the event that the system fails to detect the disturbance, appropriate action may not be undertaken and the system may not return to normal state despite manipulation. If this upset state is not managed properly, larger events may push the system into the catastrophic state. The recovery of the system depends on recovery plans and the design of the system.

Resilience in engineering is therefore often employed, not to completely avoid all threats, but to minimise failure, restoration and recovery time when disturbances do occur. For this reason, in engineering, resilience is often measured as the recovery time, or the time it takes for the system to return to normal operating conditions. The recovery of the system may be attributed to a number of factors. For instance, Dinh *et al.* (2012) suggests six principles including: flexibility, controllability, early detection, minimization of failure, limitation of effects and administrative controls/procedures in process industries. In another study Woods (2006) proposed the factors buffering capacity, flexibility, margin and tolerance. These were extended by Jackson & Ferris (2013) to form a set of principles as shown in Figure 2.3.

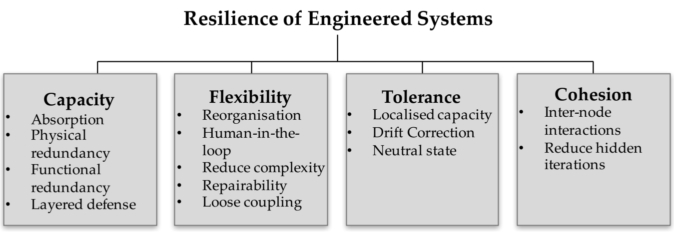


Figure 2.3. Principles of resilience engineering, adapted from Jackson & Ferris (2013)

From a change perspective, the system may be categorised to recover back to normal operating conditions in two ways: through change, or without change. Where the system does not change or react, the effects of disturbance are simply absorbed passively and may be achieved through buffering capacity (Woods, 2006), redundancy (Dalziell & McManus, 2004) or tolerance (Jackson & Ferris, 2013) which can be said to be forms of robustness. This is the first characteristic of resilience taken in this work — to absorb disturbances. Where the system does change in response to uncertainty, the response can further serve two purposes: to return the system to normal or to push the system to other performance criteria. Here, this is distinguished as "adapting to change" and "thriving for the future" respectively as summarised in Figure 2.4. These two different system responses are discussed further in the following subsections. Cases where there is a change required and the system does not respond may be seen as the system failing to meet requirements as shown in the bottom right quadrant but this is not discussed in this work.

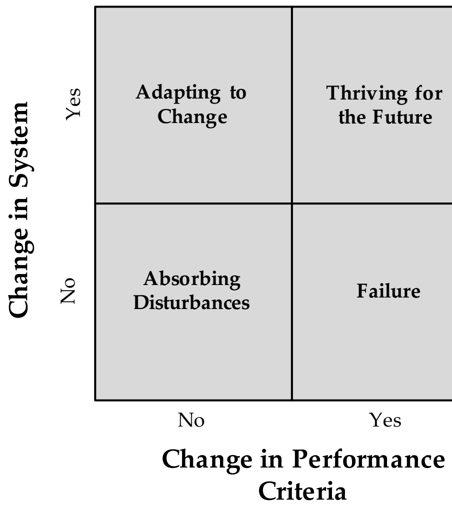


Figure 2.4. Resilience characteristics quadrant

2.1.2 Adapting to Change

Absorbing disturbances, as identified in the previous subsection, alone is not sufficient for resilience and the key factor that separates resilience from other system properties such as "brittleness" or "vulnerability" is the need for adaptive capacity to return the system to the pre-disturbed condition. This has been observed across studies on organisation management (Furniss *et al.*, 2011), systems engineering (Madni & Jackson, 2009; Neches & Madni, 2013), as well as emergency departments (Wears *et al.*, 2006) and is the second characteristic of resilience considered in this work. Adaptive capacity enables system to respond to unexpected situations and restructure rapidly to return a system to normal. From a systems engineering prespective, Dalziell & McManus (2004) captures both absorption, as described in the previous subsection, and adaptation through the definition of resilience as having "enough redundancy to provide continuity of function, or through increasing the ability and speed of the system to evolve and adapt to new situations as they arise". They further suggest that adaptive capacity can take the form of:

- Application of existing available responses to address the problem
- Application of an existing response in a new context to address the problem
- Application of novel responses to address the problem

The concepts of having both robustness to absorb perturbations and adaptability are also shown in different types of organisations, from communities to companies. At the community level, there has been research studying how resilient communities handle disaster such as in the case of Hurricane Katrina (Corey & Deitch, 2011) and the terrorist attacks of 9/11 (Coutu, 2015). In both cases, it was found having a contingency plan was a clear benefit and helped to save lives. However, another study further investigated the effect of the destruction of the Emergency Operations Centre during the 9/11 attack which disrupted planned protocols. It was found that key to maintaining operations was integrating the adaptive capacity of the response organization with the resources of New York City, private entities, and government at all levels (Kendra & Wachtendorf, 2003). These examples highlight the need to be prepared for eventualities through contingency plans, but also demonstrates that, at the same time, the ability to adapt is necessary to achieve resilience (Rose, 2004). Hémond and Benoît (2012) state "preparedness takes into account plans, procedures and measures to better respond and recover, without changing its organizational structure. In the case of resilience, the same organization will try to adapt to environmental changes (disasters or others) and to change its system to maintain an acceptable functioning". Thus instead of prescribing step-by-step plans, Somers (2009) suggests that it is better to create organisations that "demonstrate positive adaptive behaviours under stress". These examples highlight recurring concepts where there is the need to be prepared for eventualities in order to "absorb disturbances" through contingency plans but also demonstrate that the ability to "adapt for change", when there is no clear plan, is also necessary to achieve resilience (Perrings, 2006). Limnios & Mazzarol (2011) developed a Resilience Architecture Framework (RAF) and distinguishes resilience as either the "capacity for adaptive learning" or the ability to "absorb the disturbance" which are consistent with properties of adaptability and robustness respectively. Their work further names these as "offensive" and "defensive" properties respectively and warns that such attributes at the extremes may not be desirable. For example, if the organisation is too resistant to change and only absorbs change, the system may fail to recognise new opportunities. On the other extreme, an organisation cannot be too adaptable and change with every potential opportunity. Gibson & Tarrant (2010) echoes a similar view and suggests that resilience grows with time and as an organisation's resilience matures, more capabilities are added. This is illustrated in Figure 2.5. At the simplest level, resilience can be a purely reactive response such as an emergency response. This can be improved by preparing an organisation to anticipate events, such as having in place contingency plans, and at its maturity, resilience can have adaptive capabilities.

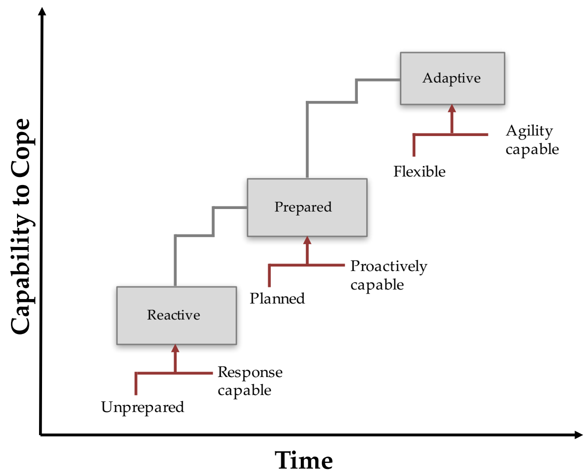


Figure 2.5. Process of resilience maturity, adapted from Gibson & Tarrant (2010)

The idea of self-organisation is prominent in autonomic systems whereby distributed computing resources adapt and make decisions automatically (Ganek & Corbi, 2003). In this context, Wódczak (2011) discusses architectures for cloud computing where the mobile network is made resilient by automatically adjusting to best fit the quality of service experienced by end users. Sterbenz *et al.* (2010) reviews the principles of resilience in communications networks and proposes 18 design principles, including autonomics for resilience. Their study further suggests that the following challenges be considered for resilient systems: understanding service requirements, normal behaviour, threat and challenge models, metrics, heterogeneity in mechanism, trust and policy, resource tradeoffs, complexity, state management, self-protection and security, connectivity and association, redundancy, diversity, multilevel resilience, context awareness, translucency, self-organising and autonomic behaviour, adaptability as well as evolvability. An ontology of resilience in network systems is further developed by Vlacheas *et al.* (2013) which considers the properties: means to achieve, domains, threats and threat agents of resilience.

Similar ideas come through when looking at cyberphysical systems and resilience serves to mitigate threats to the system (Zhu & Başar, 2011). For example, Arghandeh *et al.* (2016) develops a framework for resilience in power systems and defines resilience as the ability to recognize, adapt to, and absorb disturbances in a timely manner. Cárdenas *et al.* (2009) also holds this view on cyberphysical systems where resilience is achieved by having redundancy, diversity and adaptation of operations during attacks.

Looking at supply chain systems, a closely related term to adaptability appears: agile. Borrowing from software development frameworks, agile methodologies in supply chains allow the system to react to changes in customer behaviour and unanticipated trends in the market. In particular, Ismail *et al.* (2011) achieves resilience in such systems by incorporating agility – which itself is composed of robustness, responsiveness to market needs and pro-activeness – to find new customers. Christopher & Rutherford (2004) ties agility with the Six Sigma methodologies and suggests that resilience is where there is an optimal balance between "fat" processes with significant redundancy making them costly and overly lean processes which are vulnerable due to the lack of slack in resources. Specifically, agile is defined by Wieland & Wallenburg (2013) as, "the ability of a supply chain to rapidly respond to change by adapting its initial stable configuration".

So far it has been highlighted that resilience serves to return a system back to normal operating conditions and can be achieved through a number of factors, the most crucial of which are robustness and adaptive capacity. There may be the need to balance these factors depending on the amount of uncertainty and these factors differ through whether the system needs to change. In the robust case, the system does not change and simply absorbs disturbance. On the other hand, adaptability recovers through an actual change in the system to maintain a desired output. This could be a reorganization of resources, as typically seen in management and organizational literature, or control systems where feedback loops maintain a desired output. However, as alluded to in the end of the previous subsection, a system also can be subject to changing performance criteria over time. That is, instead of recovering to the normal state, a resilient system should also change to serve other objectives or take advantage of other opportunities in order to “thrive for the future”.

2.1.3 Thriving for the Future

The idea that resilience should incorporate not just a recovery to normal, but also the ability to evolve and capitalise on further opportunities can be seen from the shift in focus from only concentrating on the failures and risks. Hollnagel (2011) suggests that resilience should also focus on positive events and that it is easier to manage safety by “improving the number of things that go right, than by reducing the number of things that go wrong”. They further propose that four abilities are needed to realise resilience in this perspective including: the ability to respond to events, to monitor on-going developments, to anticipate future threats and opportunities and to learn from past failures and successes alike. This perspective has been more well established in ecological resilience literature where the ability to adapt is also necessary for resilience, albeit taking a slightly different view, and gives reason for including ecological studies on resilience in this literature search. From an ecological resilience perspective, adaptation refers to a system, be it species of organisms or natural systems such as lakes, and how it transitions between states of equilibria (Carpenter *et al.*, 2001). Such work concentrates on maintaining equilibrium in systems where disturbances cause, for example, a fluctuation in population numbers of interacting species. If there is a significant disturbance, an introduction of a species say, the system of species may fall into a different set of equilibria which can then lead to the extinction of another species. Therefore, adaptation in the ecological sense refers to reorganisation of the ecosystem and resilience is defined as the “ability to absorb change and disturbance and still maintain the same relationships between populations or state variable” (Holling, 1973). With such a definition, resilience in ecology is measured by the amount of disturbance the system can take until the system changes or "flips" to another equilibrium (Derissen *et al.*, 2011; Walker *et al.*, 2004). This further juxtaposes the idea of stability and adaptability. In a stable system, the amplitude of the oscillations decreases to a constant sustained value for each population and is thus defined as the ability "to return to an equilibrium state after a temporary disturbance". This definition is similar to the earlier concept of robustness where change is absorbed through some tolerance. However, where this differs from engineering is that, in engineering, when the system is over-stressed or pushed outside the designed limits, it generally fails. For example, if a bridge is overloaded, it may collapse. In ecology, however, multiple equilibria or system states may exist and when a species becomes extinct, it is common for another species to flourish and thrive. Adaptation in this sense is the reorganisation of species so that, at least for some, new opportunities may be taken advantage of when it presents itself.

Translating this into a corporate ecosystem, when one business fails another may take its place. Resilience in this sense is not just about managing the challenges businesses face, but also navigating the changing circumstances with new competitors, customer preferences and opportunities. As such, resilience also involves adapting business practises and resources such that companies can effectively transition between "system states" with changing performance to keep competitive and so that it too can "thrive" (Hamel & Välikangas, 2003). Furthermore, with this concept of changing system states, there has also been a change in sentiment: Resilience has traditionally been thought of as a response to adversity, but now it includes a more positive view where it serves to grow a system for new opportunities. In management literature this is illustrated by Dalziell & McManus (2004) in Figure 2.6.

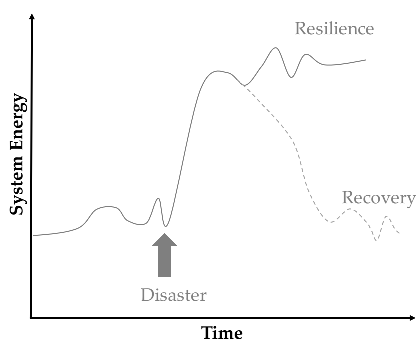


Figure 2.6. Resilience illustrated as a system moving between multiple equilibrium states and not necessarily back to pre-disaster conditions, adapted from Dalziell & McManus (2004)

The figure illustrates the idea of resilience being the adaptation to a new state, similar to the thinking from ecological studies, and suggests that organisations are complex self-organising systems with multiple equilibrium states. The system energy represents the current system condition and in the event of some disaster, resilience allows the system to move to other states instead of returning the system's to the pre-disaster condition, where the same crises may again manifest.

Returning to engineering conceptualisations, another visualisation of this idea whereby resilience requires an evolution of the system is given by Woods & Wreathall (2008) who gives an analogy using stress-strain plots. Their concept is borrowed from material science and describes how a material responds to external force by either bending or breaking. In stress-strain plots, materials exhibit two different types of behaviour giving an elastic region, where the material stretches uniformly with increasing load, and a plastic region, where the material stretches non-uniformly with increasing load. The elastic region is shown by a straight solid line in the Figure 2.7 while the plastic region is shown by the curve at the top. If stress exceeds the plastic region, the material fails as shown by the cross. As the capabilities of a system are exceeded in the plastic region, active steps are needed to extend the ability of the system before it fails. These actions may take the form of adding resources or new strategies so that the system can continue to stretch and is represented by the additional dotted curves. This emphasises that resilience allows the system to be continually improved and perform in conditions that may not have been previously anticipated.

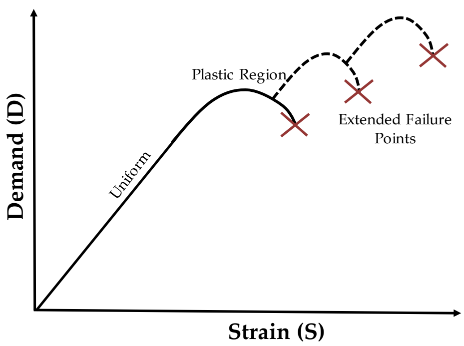


Figure 2.7. Resilience stress-strain plots, adapted from Woods & Wreathall (2008)

This is similarly illustrated by Fiksel (2003) who uses thermodynamic systems to represent different types of resilience as shown in Figure 2.8. In this diagram, each system has a stable state representing the lowest potential energy at which the system maintains function. When subject to some disturbance, the system can be thought of as a ball pushed up the slope of a pit. Essentially, resilience may be thought of as the width of the pit representing the different disturbances it can handle and the stability is illustrated by the gradient of the slopes showing the speed at which the system returns to equilibrium (Gunderson, 2000). In the resistant system depicted on the left, the system operates in a narrow band of possible states and thus the system is not resilient as it cannot handle many different events. The system, however, may be stable. The middle illustration is resilient to disturbances as it is able to retain function across a large range of possible states, albeit with a slower return to equilibrium. The right-most diagram also shows resilience, but with multiple equilibrium states which can be transitioned between with a sufficiently large disturbance. This is similar to the conceptualisations found in ecology where a shift to a different equilibrium also represents a change in the system structure and function. These studies gives another important perspective on resilience and forms the third and final characteristic of resilience used in this work: the need evolve, take advantage of other opportunities and ultimately “thrive for the future”.

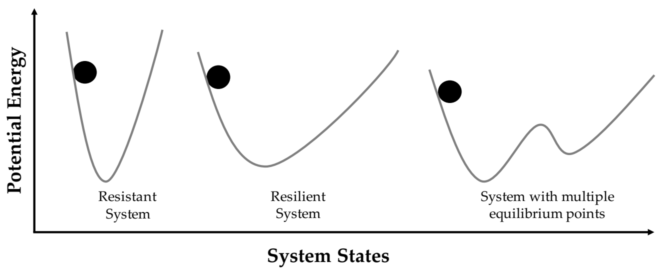


Figure 2.8. Thermodynamic analogy of resilience, adapted from Fiksel (2003)

2.2 Designing for Resilience

Now, having explored the work and definitions of resilience, the challenge of this work is to endow a system with the characteristics as defined in the previous section from an engineering design perspective. The previous section identified the characteristics of: absorbing disturbances, adapting to change and thriving for the future. Underpinning these ideas is how the system responds and changes when faced with uncertainty. In the first case, the system simply does not respond, and instead passively absorbs uncertainties. For example, many engineering systems are designed with a margin of safety to accommodate fluctuating loads such as in buildings and civil structures. The latter two characteristics then involve some response from the system: adapting is distinguished by some response which returns the system to normal while thriving is where the system itself restructures or reorganises for some new environment, opportunity or criteria.

As such, further literature from engineering design and engineering change management is now consulted to find the state-of-the-art solutions for embedding these characteristics into systems and to understand how systems can be designed to manage change. From engineering design, systems can be designed to exhibit properties often referred to as ilities and examples include: robustness, versatility, changeability, flexibility, scalability, modularity and survivability *etc* (Chalupnik *et al.*, 2013; McManus *et al.*, 2007; Taysom & Crilly, 2017). This list is not exhaustive and as with resilience, there is much debate over the semantics and factors for each ility. Furthermore, some properties may be composed of a set of ilities and Ross (2014a) suggests that resilience requires the combination of flexibility, robustness and protection. Various ilities were reviewed in literature and the three characteristics from the previous subsection have been found to correspond to the ilities: robustness, adaptability and flexibility. Robustness was selected to address the first concept of “bouncing back” and passively recovering from disturbances. Indeed, some of the resilience literature mentions robustness specifically as a component of resilience (Longstaff *et al.*, 2013; Spero *et al.*, 2014). Likewise, adaptability has been much discussed in resilience literature and therefore warrants inclusion (Gallopín, 2006; Limnios & Mazzarol, 2011; Walker & Meyers, 2004). The final characteristic of “thriving for the future” is mapped to flexibility which should be used cautiously since adaptability and flexibility are often used interchangeably. There is, however, literature that discusses the differences between the two (Ross, 2006). These ilities are now explored in the next subsection to understand their properties and how the relationship between these concepts can attribute to resilience in infrastructure systems.

2.2.1 Robustness

Redundancy, tolerance and margins were identified as factors through which to achieve resilience. In engineering design, these methods are associated with robust designs and thus robustness forms one of the requirements for resilience. Robustness gained attention through Taguchi's (1985) seminal work in controlling quality in product manufacture. Variations in quality were attributed to noise factors and thus robustness is where "the product's functional characteristic is not sensitive to variations in the noise factors". In Taguchi's work, robustness is applied by reducing deviation from a target value and realised through system design, parameter design and tolerance design. System design involves choosing materials, components and connections for basic design. Through parameter design, parts are chosen to allow the system to perform as uniformly as possible and is usually carried out by investigating the relationship of noise and design parameters in order to minimise the sensitivity to noise. Tolerance design selects the appropriate grade of components to remove variation. Taguchi's methods were based on Fisher's statistical work (1949) on the Design of Experiments which focused on how to carry out experiments in the presence of variation. From this work, robustness may generally be seen as the ability to be "insensitive towards changing environments" (Fricke & Schulz, 2005). That is, the system does not respond to disturbances in the environment, neither changing any processes nor properties, yet maintains the required output or performance.

As an example of infrastructure systems, bridges need to be robust so that it withstands extra loading from increased traffic or fluctuations in wind speed/direction. It is generally designed with extra strength to tolerate some predicted margin of error without collapsing. Another example could be the maximum take-off weight for aircraft where aircraft are designed to operate with weight loadings under a certain threshold. While robust designs may be more cost efficient when the disturbances are predictable, they may fail if there are substantial, unexpected influences on the system that push the system outside the designed margins. As such, robustness is better suited for systems where the uncertainties are relatively more understood, typically in the near future, or where the demands of the system are unlikely to change throughout the system lifecycle. However, infrastructure systems are usually complex and system lifecycles tend to span over 10 years making uncertainties difficult, if not impossible, to predict. Coupled with the fact that infrastructure systems often involve interactions with multiple stakeholders with changing requirements, a robust design is usually necessary but not a sufficient condition nor cost efficient to protect against all eventualities. Resilience, therefore, not only requires the system to be able to accommodate predictable uncertainties through robust design, but also allow for change and evolution of the system. This is addressed through adaptability and flexibility as follows.

2.2.2 Adaptability

Over the lifecycle of a system, the designed margins of a solely robust solution may be exceeded and therefore the system must change to maintain satisfactory performance or succumb to failure. This may be considered through the properties of adaptability and flexibility. There is, however, a lack of consensus concerning these definitions in literature and these two terms are often used synonymously to broadly denote change in a system. In resilience literature as discussed previously, two concepts linked with adaptability have emerged: to adapt the system to recover to a normal state, or for the system to adapt to another state altogether as discovered in ecological studies. In engineering design, adaptability can also refer to design adaptability or product adaptability which addresses the reuse of a design or the ability of the product to be changed to have alternate capabilities respectively (Gu *et al.*, 2004). These forms of adaptability may be achieved through platforms, modular and adaptable interfaces as well as functional and physical structure independence. However, these same concepts and methods are also associated with flexibility in engineering design which leads to semantic difficulties (Harper, 2011; Suh *et al.*, 2007).

Here, the terms adaptability and flexibility are further distinguished by the location of the change agent following from work by Fricke & Schulz (2005) and Ross (2003). From this work, adaptability is where the change agent is internal to the system and flexibility is external to the system. An internal change agent is where the change is instigated from within the system and adaptability automatically, without the need for external action, serves to move the system back to a previous normal performance level. This is opposed to an external change agent, considered in flexible design, where an external decision maker changes the requirements of the system. An example, given by Shah *et al.* (2008) considers cooking popcorn in a microwave. The system boundary can be defined as the microwave with popcorn inside and with everything else external. For an adaptable system, the microwave heats the popcorn with some program and feedback to determine whether it is finished cooking. In this case, the definition of "cooked" is determined by the microwave settings internal to the system and cooking temperature is controlled via some feedback loop. For a flexible system, the microwave heats until an external decision-maker determines the popcorn is cooked and stops the microwave. From these definitions, it may be seen that adaptability relates to the concept in resilience whereby adaptation serves to keep the system within some pre-defined state, or in the above example, pre-programmed state. Flexibility relates to the idea of adapting to different states since it allows agents to decide whether the state is appropriate, or in the case of popcorn, whether the popcorn is cooked sufficiently. An adaptable system is therefore a system that "delivers their intended functionality under varying operating conditions through changing themselves ... no changes from external have to be implemented into such systems to cope with changing environments" (Fricke & Schulz, 2005). This is similar to the Design for Adaptability framework where control and feedback are used to modify system performance (Kasarda *et al.*, 2007). The system can respond to changing inputs through control algorithms such as look-up tables, fuzzy logic or standard linear control algorithms. Another example could be an aircraft which maintains stability and adapt to changes in flight conditions through a lookup table of stability derivatives (Stevens *et al.*, 2015). In this case, actuator positions are automatically adjusted as a function of flight conditions. This is useful in high-risk situation where immediate responses are needed instead of waiting for human intervention (Neches & Madni, 2013). For telecommunications infrastructure, this could be the automatic re-routing of network traffic based on the current demand (Myslitski *et al.*, 2017).

Since the changes occur automatically in these system, these changes must be planned and anticipated during the conceptual design stage so that the system continues to operate within the required boundaries. Indeed, some unforeseen event could still push the system outside these initial design boundaries which cannot be automatically rectified leading to failure. In the case of an aircraft autopilot, although it can be designed to handle a range of conditions, some unforeseen event could still push the aircraft outside designed performance limits or outside the flight envelope where it cannot be automatically corrected by the system, leading to failure.

An adaptable design is therefore useful where it is impractical or costly to make the system excessively robust through large redundancies and instead allows the system to change automatically to return to normal. This requires some foresight into the environment in which the system is deployed and therefore may be useful, as similarly for robust designs, where uncertainties are relatively more understood in the near future or where the demands on the system is unlikely to change throughout the lifecycle.

2.2.3 Flexibility

In the event a substantial change or upgrade is required for the system, a flexible design may be adopted. This allows the system to change for new opportunities or to accommodate disturbances which the system was not originally designed. Flexibility, in this sense, is akin to ecological resilience literature and therefore contrasts with robustness and adaptability in that it does not serve to maintain normal operations, but instead, it allows the system to change its performance boundaries so that the system can evolve. The concept of flexibility and adaptability may also be distinguished by the location of the change agent. In the adaptable case, the change agent is located within the system leading to automatic change. On the other hand, the flexible system has the change agent external to the system and allows a decision maker to change the requirements of the system (Ross, 2006). The definition of flexibility is taken as "a system's ability to be changed easily. Changes from external have to be implemented to cope with changing environments" (Fricke & Schulz, 2005). A flexible system may therefore be designed so that it has a number of options for the decision maker and flexibility makes it easy to change or upgrade these options when appropriate. Some applications of flexibility in engineering systems include: designing a plant that can produce the same product from various types of feedstock, a heat exchange network that can output temperature specifications from different inputs (Dinh *et al.*, 2012), or an aircraft autopilot being reprogrammed for a different heading or flight path settings. From a product view, this could be a screwdriver with changeable multi-bits for different screw types (Rajan *et al.*, 2005). In this case, there are options for the decision-maker: the multi-bit appropriate for the task.

Flexibility may be achieved through modularity, platform design and interface design. Modularity involves segregating the system architecture so that independent modules are formed. Platform design focuses on using a common base platform for multiple designs to lower costs. Interface design focuses on standardising the connections between modules for compatibility. Analysis may involve examining the dependencies within the system architecture which can be visualised through matrices such as the Design Structure Matrix (DSM). In particular, Suh *et al.* (2007) suggests that components that are multipliers, ones that instigate more change than receive, are prime targets for flexible design (Eckert *et al.*, 2004).

Flexible designs are therefore especially important where the requirements could change in future. For infrastructure engineering systems, which typically lasts more than 10 years, it is likely that there will be changes to demand and requirements over their lifecycles. As such, flexibility may be employed for an engineering system which faces high uncertainty, where uncertainties are hard to predict and where it is impractical to use an excessively robust design. By enabling the system to be changed for different requirements, it allows a system to evolve and potentially thrive when faced with substantial changes in demand.

2.2.4 A Conceptual Model of Resilience

It is apparent that each life-cycle property accommodates differing amounts of uncertainty and is integral in making up the facets of resilience. These properties and concepts of resilience can be amalgamated into a definition which is used for this work moving forward, given as:

> **Resilience Definition**
> Resilience is the system's response to uncertainty, be it risk or opportunity, through both robust and flexible strategies such that it continues to function to the fullest possible extent over time.

This definition differs from others through the encapsulation of both risk and opportunity through robust and flexible design strategies. Infrastructure systems are inherently sociotechnical and subject to a range of uncertainties and thus the specific definition of uncertainty is deliberately left open. Furthermore, this allows the definition to be applied to other domains and not just for engineering. For the case studies presented in Chapter 6, uncertainty is taken to be the demand on a Waste-to-Energy and a telecommunications infrastructure system. Relating all of these design properties to uncertainties, each property may be visualised by some performance envelope. For instance, a robust system can only handle a margin of uncertainty that was designed into the system and should have sufficient redundancy to withstand foreseen disturbances without the need for change. Once the system is deployed, these margins are fixed and cannot be changed without replacing the system. Adaptability, which serves to return the system back to normal, is similar in that the design also only tolerates some preconceived uncertainty margins and performances that were designed into the system. Although the system itself can change and adapt, there are operating bounds that have to be considered at the conceptual design stage. This initial understanding of the uncertainty margins during the conceptual design stage is termed here, the "initial robust bound" and shows the performance envelope of the system which includes robust and adaptable strategies as shown by a dashed line in Figure 2.9. The size of the performance envelope thus represents the amount of uncertainty the system can handle. The figure further depicts an initial design with some robust boundary illustrated by a red circle. Through adaptation, an adapted design can be reached which has another robust boundary and may have a boundary that is separate (Figure 2.9.a) or in union (Figure 2.9.b) with the initial design boundary. Although there is change, there is no need for external action from a decision maker and thus all adaptable designs must be foreseen at the time of design. There may be several adapted designs, which have not been shown for clarity, and the union of all robust boundaries at the point of deployment for all preconceived designs, including the adapted designs, form the initial robust boundary. If the system is not designed to be adaptable, then the robustness of the system becomes the initial robust boundary. This initial robust boundary gives the performance envelope at the point of deployment and thus may be thought of the "total" robustness of the system which accounts for both robust and adaptable strategies.

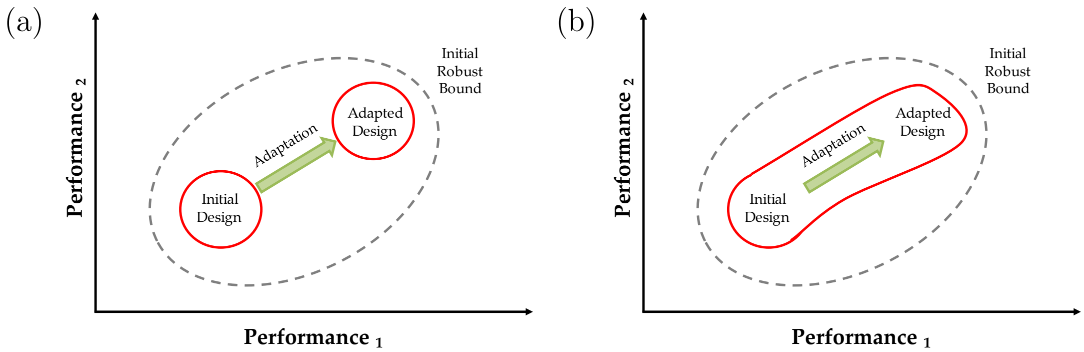


Figure 2.9. (a) Performance boundaries of robustness and adaptability with separate performance envelopes. (b) Performance boundaries of robustness and adaptability with performance envelopes in union.

For example, consider a passenger aircraft, designed with some performance envelope as per the initial design. Figure 2.9.a could illustrate an event of a primary source electrical failure and adaptability in this case would be the automatic switching from the main power source to backup generators in order to maintain flight. Due to the reduced power availability, the performance may be compromised with some functions unusable, thus giving a separate performance boundary. This adapted design boundary, however, still lies within the initial robust bound since engineers have designed the aircraft for failure scenarios at the conceptual stage. In the case of Figure 2.9.b, this could be illustrative of an aircraft maintaining its pitch. The initial design may be the robustness of the aircraft subject to gusts and still maintain the same pitch without the need to change. An aircraft is designed to have natural stability such that if the nose is pushed up, there should be a natural tendency for the aircraft to push the nose down without any action from the autopilot or pilot. There could be, however, turbulence which pushes the aircraft out of the robust bound such that it requires autopilot intervention to adjust the flaps and maintain pitch. This automatic change in the system allows the aircraft to operate in a larger envelope of conditions, say wind speed, and is thus represented as the union of the natural stability of the aircraft and autopilot intervention. The initial robust bound would therefore be the total performance for all designed configurations.

Flexibility, on the other hand, allows for the system to operate in conditions that were not designed for in the initial robust bound. It may be pre-empted that the requirements, and thus the performance envelope, may be subject to change in the future, but the initial robust bound would not be able to accommodate these new requirements. Therefore, flexibility is needed once the system is deployed and has to operate outside this initial robust boundary as shown in Figure 2.10.

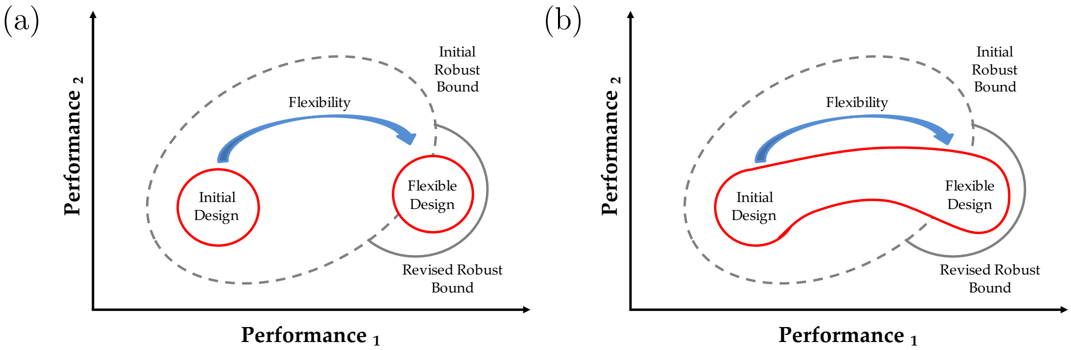


Figure 2.10. (a) Performance boundaries of flexibility with separate performance envelopes. (b) Performance boundaries of flexibility with performance envelopes in union.

The initial robust bound, as before, represents the boundaries for robustness and adaptability and encompasses all design configurations when the system is deployed. Flexibility serves to modify this initial robust bound in some way and by doing so, creates a revised robust bound. As before, this new performance boundary may be separate (Figure 2.10.a) or in union (Figure 2.10.b) with the initial design. Taking the passenger aircraft example, Figure 2.10.a could be to re-purpose as a cargo aircraft such that the operating criteria are different. In the case of Figure 2.10.b, this could be a retrofit where more passengers could be carried. This is a union of the performance envelope since, assuming that there is an increase of the number of passengers, the original number of passengers could also be served.

The previous discussion relates the three properties through uncertainty and performance. However, it is also important to note that these properties are also related through time. Robustness and adaptability are suitable predominantly in the near future, where the range of operations can be forecast and to ensure the system can handle the range of predicted conditions. Flexibility is more important when considering the strategic aims of a system where decision makers are given the choice of changing the requirements and performance of the system in the unforeseen future (de Neufville *et al.*, 2004). This is particularly important for resilience in engineering infrastructure systems since the system has to be designed to withstand uncertainties that are predicted in the near future, yet also evolve for any opportunities that may arise. The evolution of the system properties through time can then be illustrated by Figure 2.11. The figure shows how a system can continue evolving through transitioning between uncertainty bounds. R_x and A_x represent robustness and adaptability respectively with the subscript indicating the robust bound of the design. F_x represents flexibility and the subscript indicates the transition between the bounds to evolve through time.

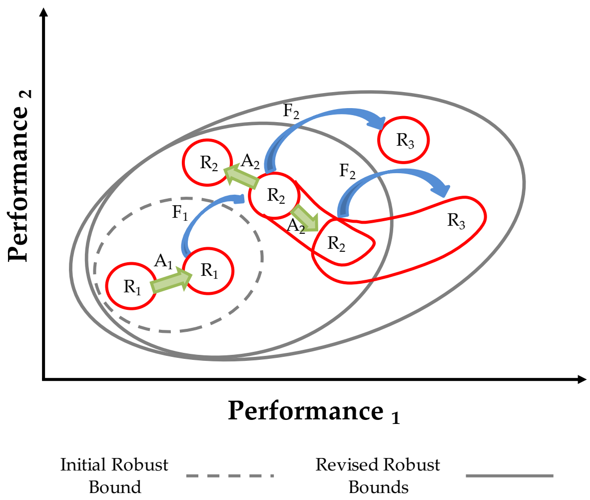


Figure 2.11. Conceptual model showing evolution between system properties

For engineering infrastructure systems, selecting the appropriate designs and transition paths is therefore critical for resilience due to the long lifecycles involved. Furthermore, while there has been substantial work done in understanding how resilience is necessary to maintain the status quo within each of these robust bounds, from a strategic change perspective, it is important to understand the size of the bounds of each design and how to upgrade between these performance envelopes when necessary. As the system is upgraded, there then becomes some new boundaries for the uncertainty and performance envelope for the new design. de Neufville & Scholtes (2011) highlights the importance of strategic upgrades through a parking garage example and shows how flexible phased investments can mitigate the asymmetric risk of investment whilst allowing the system to take advantage of opportunities. Similarly, in the Tagus River bridge example, risk is lowered by only installing a second deck only when demand is sufficient and de Weck *et al.* (2004) showed that a flexible phased deployment of the Iridium satellites could have saved 20% in cost.

Although the merits of strategic flexible approaches have been highlighted, it is argued here that resilience requires the balancing of both initial robustness (incorporating both robustness and adaptability) and flexibility. That is, how large should these initial robust bounds be? And how much should be left for future upgrades? If the demands or uncertainties are relatively constant over time, it may be cheaper to have a one-off robust solution than to excessively upgrade. The cost of each upgrade must therefore also be taken into account and amount of redundancy in robust solutions must be optimised. On the other hand, optimizing systems could also mean reducing redundancy, as advocated by lean methodologies, and can lead to more fragile systems which are unable to cope with unexpected fluctuations due to the lack of excess resources (Christopher & Peck, 2004).

Further work for this thesis therefore requires an understanding of the trade-offs between the sizes of the uncertainty bounds in robust and flexible designs in order to achieve resilience. From previous discussion, these bounds should further not only focus on negative risk but also allow for the transition for new opportunities. The final part of the literature review in this chapter therefore examines how previous studies have measured and assessed resilience so that these uncertainty bounds can be investigated.

2.3 Evaluating Resilience

Having defined the concepts for resilient engineering infrastructure systems in the previous sections, existing models for evaluating resilience are now discussed. In particular, the previous search identified the need for robustness, adaptability and flexibility in order to achieve resilience. Through abstraction and relating these properties through uncertainty, which is integral to resilience, each design solution can be thought of as having some initial robustness (incorporating robustness and adaptability to maintain normal operations) and flexibility bounds. Thus an approach is sought where the bounds of each design and the effective transitioning between a number of designs can be assessed. Models from resilience literature are explored broadly in this subsection, looking at both qualitative and quantitative methods, so as to provide a wider view of the resilience landscape in case similar concepts have already been addressed. Complementary approaches from engineering design are further presented in Chapter 4.

2.3.1 Qualitative Approaches

There has been substantial literature attempting to define the concept of resilience for a number of domains, but much less work in terms of assessment of resilience. As seen in some of the studies presented in the previous sections, resilience can be decomposed into several factors. Qualitative approaches often measure these factors through surveys and aggregate these scores to assess resilience. This approach is often found in the organisational literature where the factors are more difficult to quantify. For example, governments have taken interest in resilience in order to tackle risks such as nuclear and chemical disasters, water pollution, deforestation, climate change and terrorism (New Zealand Government Ministry of Civil Defence & Emergency Management, 2009; United Nations Office for Disaster Risk Reduction, 2005). New Zealand's approach to risk incorporates resilience, defined as "the society's ability to withstand, recover from and thrive after a major impact (disaster)" and may be achieved by the 4Rs: reduction, readiness, response and recovery (Seville, 2009). These echo the findings in the resilience literature discussed previously. In order to achieve this, McManus (2008) surveyed organisations in New Zealand and further identified 15 resilience indicators, categorised into Situation Awareness, Keystone Vulnerabilities and Adaptive Capacity. This was extended to incorporate 23 indicators of resilience split into 4 groups: Resilience Ethos, Situation Awareness, Keystone Vulnerabilities and Adaptive Capacity as presented in Table 2.4. These factors were then formed into a survey tool where organisations can benchmark resilience by scoring against each factor. This resilience model was further extended by Lee *et al.* (2013) which emphasised the need for a two pronged approach consisting of adaptive capacity and planning.

Table 2.4. Resilience Indicators from McManus (2008)

Indicators of Resilience	
Resilience Ethos	• Commitment to resilience • Network Perspective
Situation Awareness	• Internal & External Situation Monitoring • Informed Decision Making • Recovery Priorities • Understanding & Analysis of Hazards & Consequences • Connectivity Awareness • Roles & Responsibilities • Insurance Awareness
Management of Keystone Vulnerabilities	• Robust Processes for Identifying Vulnerabilities • Planning Strategies • Participation in Exercises • Capability & Capacity of Internal Resources • Capability & Capacity of External Resources • Organisational Connectivity • Staff Engagement
Adaptive Capacity	• Strategic Vision • Leadership, Management & Governance • Minimisation of Silo Mentality • Communications & Relationships • Information & Knowledge • Innovation & Creativity • Devolved & Responsive Decision Making

Another framework has been developed by Madni & Jackson (2009) based on four key pillars: disruptions, system attributes, methods, and metrics. This allows system engineers to focus on the impacted system attributes, where resilience is needed, methods to achieve resilience in the relevant system attributes, and what resilience measures are appropriate. From resilience engineering, Hollnagel *et al.* (2006) describes three kinds of common accident models as the simple linear model, the complex linear model and the systemic non-linear model. The first looks at cause-effect in event chains to analyse a "domino-effect" while the second focuses on combinations of unsafe acts and observations of deviation. The last type looks at how combinations and variations of normal events give rise to negative events. In particular, the Functional Resonance Analysis Method (FRAM) developed by Hollnagel (2016) was applied to the Alaska Airlines

Flight 261 accident to analyse resilience (Woltjer, 2008) as shown in Figure 2.12. FRAM comprises four steps: 1) identifying and categorising system functions into six basic parameters of input, output, preconditions, resources, time and control 2) characterising the potential variability of the parameters 3) defining the functional resonance based on possible dependencies between functions 4) identifying the barriers for variability that may prevent unwanted events from occurring. In the diagram, function of the system is represented by a hexagon with each vertex representing one of the six basic parameters of input, output, preconditions, resources, time and control. The parameters for each function are then connected by a line if some relationship exists. For the case of accident analysis, the functions that failed can be examined to understand how it affects the system as a whole so that preventative measures can be taken.

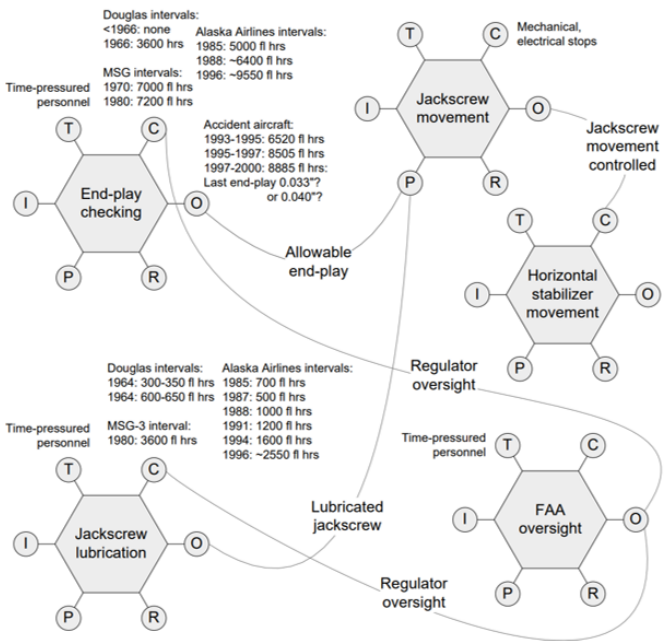


Figure 2.12. Functional Resonance Analysis Method applied to Alaska Airlines Flight 261 accident, adapted from Woltjer (2008)

2.3.2 Quantitative Approaches

There has been a number of quantitative approaches proposed to measure resilience. For example, system dynamic models have been used for modelling supply chain resilience (Sheffi, 2005), mathematical models used for network analysis (Roberto & Silva, 2014) and petrochemical supply chains (Vugrin *et al.*, 2010). Bayesian Networks have been applied to inland water ports (Hosseini &

Barker, 2016) and genetic algorithms have been used to model infrastructure restoration (Ouyang & Wang, 2015). A more extensive review of quantitative methods for resilience can be found from Hosseini *et al.* (2016). In such cases, resilience has usually been measured by the time it takes for the system to return to normal or recover following some disturbance, giving rise to the "resilience triangle". Bruneau *et al.* (2004) uses this to describe how infrastructure systems lose functionality following some disaster, such as earthquakes, in their study. Resilience enhancement therefore reduces the size of the triangle as shown in Figure 2.13.

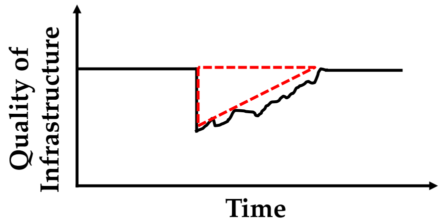


Figure 2.13. Resilience Triangle showing recovery after disturbance, adapted from Bruneau *et al.* (2004)

A similar approach has been developed by Pflanz & Levis (2012) for a civilian infrastructures where the system response, or Measure of Performance (MoP), is modelled through Petri-Nets. This is shown in Figure 2.14. The system is disturbed and measurements are taken from the response of the system to calculate various metrics such as capacity, tolerance and flexibility which attribute to resilience.

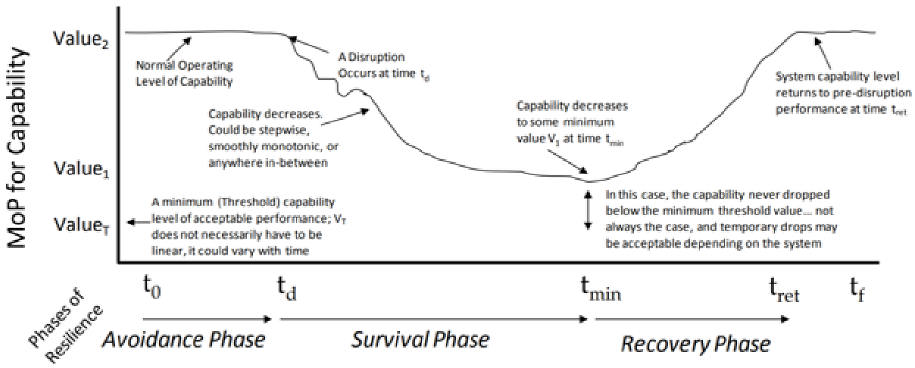


Figure 2.14. Change in Measure of Performance following disruption, adapted from Pflanz & Levis (2012)

This exploration of the solution space is akin to the trade space approach for resilience suggested by Spero *et al.* (2014) where alternate solution sets, similar to alternate system states in resilience terms, are analysed. A trade space is a "multidimensional solution space in which information about design alternatives is displayed in order to allow decision makers to investigate how much capability in one metric must be given up in exchange for a specified capability in another metric". This generates a large number of alternative designs through guided automated search for the identification of high-impact variables (Neches & Madni, 2013). A workshop attended by 40 academic, government, and industry researchers was also organised by Spero *et al.* (2014) to develop trade space technology research recommendations for Engineered Resilient Systems. It was concluded that there are issues regarding "uncertainty propagation, subjective data, high-dimensional spaces, static and flat visualizations, combinatorial what-if scenarios, feature identification, and retention of data throughout a lifecycle have not been sufficiently addressed." These further exist due to differences in lexicon between groups.

Further tools have been developed to benchmark an organisation's resilience so that it can be improved. A mathematical evaluation of organizational resilience potential using fuzzy sets was developed by Aleksić *et al.* (2013) while Pal (2013) measured an organisation's resilience though the Altman's Z score, a financial indicator, to predict the probability a firm will become bankrupt within the next two years. Studies have also been conducted on building resilient supply chains and modelling the dynamics of the system (Sheffi, 2005). For instance, one study simulated a Portuguese automotive supply chain to evaluate alternative supply chain scenarios in response to a disturbance and to understand mitigation strategies affecting supply chain performance (Carvalho *et al.*, 2012). This view of resilience is similar to that presented in other domains in that resilience is the "ability to react to an unforeseen disturbance and to return quickly to their original state or move to a new, more advantageous one after suffering the disturbance". The performance measures used were lead time ratio, the ratio between the actual and promised lead time, and the total cost. Flexible and robust strategies in the form of restructuring transport and redundancy respectively were tested to mitigate the disturbance and were found to be valuable. Work by Ng and Sy treats the supply chain as a dynamic system and builds a systems dynamics model to examine transient behaviour in workforce inventory control after some disturbance (Ng & Sy, 2014). The supply chain is based on a study by Saleh *et al.* (2010) and illustrated in Figure 2.15. A search algorithm was then developed to optimise for resilience by maximising the amount of uncertainty the system can handle and still guarantee performance. This definition of resilience is similar to those uncovered in ecological studies.

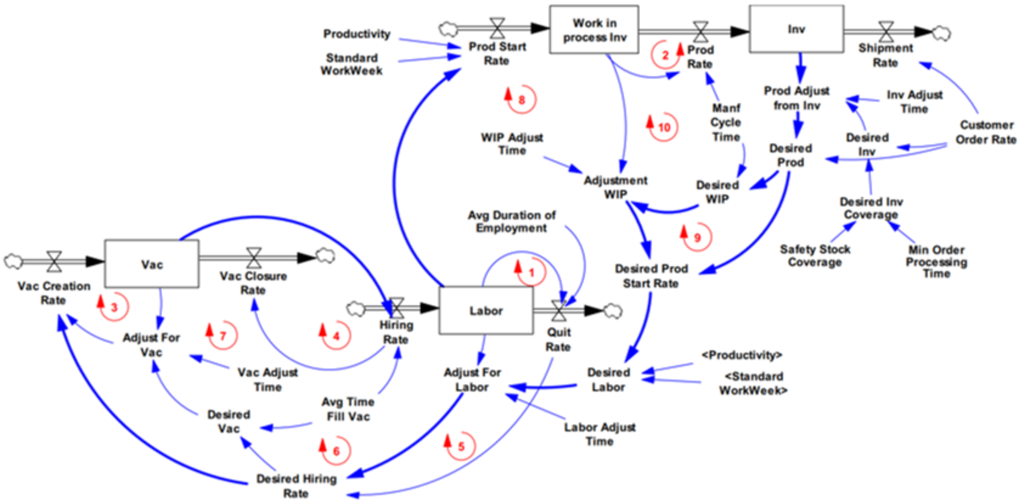


Figure 2.15. Modelling supply chain through system dyanamics, adapted from Saleh *et al.* (2010)

Systems dynamics models have also found use in ecological studies where resilience is measured by the amount of disturbance that cause system dynamic models to change (Derissen *et al.*, 2011). The eigenvalues in system dynamics models may also be used to find the response to disturbances much like in stability analyses (Neubert & Caswell, 1997). Another study uses agent models to understand how rangeland populations interact with each other (Janssen *et al.*, 2000) and Higgins *et al.* (2010) proposes multi-agent modelling, dynamic systems and network theory to simulate agricultural value chains.

2.4 Research Gap for Resilience & Infrastructure Systems

This chapter has examined extant resilience literature to identify a research gap for further work. A significant number of studies have been found in establishing the definition and the factors that influence resilience from a wide range of domains, most notably ecology, organisational management and engineering. The review then distilled these concepts that describe resilience into three characteristics: absorbing disturbances, adapting to change and thriving for the future. While further nuances of these definitions could be elicited, how these properties can be translated into pragmatically improving systems have received less attention (Bhamra *et al.*, 2011) and have been chosen for further attention. To this end, these characteristics were then mapped onto three engineering design ilities: robustness, adaptability and flexibility respectively. A conceptual model further explored the relationship between these properties from a change and uncertainty perspective which fundamentally underpins resilience. It is suggested that all designs have some initial robust bound where both robust and adaptable strategies serve to maintain the system's performance within some performance envelope. These are fixed once the system is installed and the amount of uncertainty that can be accommodated must be predicted during conceptualisation so that the system does not fail in operation. For this reason, robust and adaptable strategies are useful where the uncertainties are predictable such as in the near future. Where the uncertainties are not easily forecast, a flexible approach, which allows for the performance bounds to change, may be better.

From this, it is apparent that these strategies should be balanced depending on the system's circumstances. Especially for infrastructure systems, it may be impractical to continuously keep switching between components as per an adaptable strategy. For example, it can be difficult for road networks or power plants to frequently change assets and are generally fixed once installed. The balance, or trade-off, thus concerns how much uncertainty the system should be designed for now, and how much to leave for future upgrades of the system. This is conceptualised in the model through the "initial robustness" which describes the total uncertainty envelope that a system can operate at the time of deployment whereas flexibility functions as a means to transition between designs. Robustness, hereafter, refers to this "initial robustness" and accounts for both robust and adaptable strategies which give some total robustness at the time of deployment.

This gives a more strategic view of resilience compared to traditional concepts where resilience serves to return a system to normal and further allows conceptualises how a system may change for new opportunities. While this approach is similar to ecological studies where ecosystems can transition from state to state following some disturbance, this perspective is less common in engineering studies. To the author's knowledge, this strategic approach to resilience in engineering infrastructure systems has not yet been explored and is especially relevant to infrastructure systems where long lifecycles can lead to changing requirements. The traditional view, accounting for operational day-to-day uncertainties through robustness, is therefore balanced with the need for strategic change through flexibility in infrastructure systems. Following on from this, assuming that the system will need to change at some point, the optimal timing of the change should be explored.

With this perspective, an approach to assess different designs and uncertainty bounds is needed to understand how to effectively move between designs. Numerous qualitative and quantitative approaches from resilience literature were further examined, but none were found to satisfactorily take this strategic approach for engineering systems. Trade space studies, however, were found to be a useful concept to compare a large number of designs which is necessary in this study and could potentially be used to understand the thresholds between robustness and flexibility. From a business point of view, this reflects the trade-off between large one-off upfront investments, as in the robust case, compared to continuous investments over time, as per the flexible strategy. Furthermore, simulations, models and benchmarks can used to support business cases and demonstrate the need to become more resilient, making this relevant for this work's industrial sponsor. A similar quantitative approach would therefore be ideal moving forwards. As such, further work would involve developing a quantitative resilience assessment method to satisfy the following conceptual requirement:

Conceptual Requirement

- To understand the trade-off between robustness and flexibility in designing resilient engineering infrastructure systems

This work therefore aims to address the research gap in understanding the strategic view of resilience in engineering infrastructure systems. In doing so, contributions of this work will involve understanding the trade-off between robustness and flexibility. Furthermore, by being able to quantify this trade-off allows different design options to be compared and provide decision makers guidance into how to best architect systems for resilience. This leads to three objectives which need to be addressed in this work: 1) To develop a quantitative evaluation method for resilience in engineering infrastructure systems, 2) To understand how design strategies affect resilience in engineering infrastructure systems and 3) To providing guidance for decision makers to enable resilience in engineering infrastructure systems. Since there so far has not been a method found from resilience literature to satisfy these requirements, Chapter 4 draws inspiration from engineering design methods to explore other solutions.

2.5 Summary

This chapter presents a literature review to explore the current concepts of resilience and serves to identify further work for this thesis. First, the characteristics of resilience were examined from engineering, organisational management and ecological literature before being grouped into three main concepts: absorbing disturbances, adapting to change and thriving for the future. In the traditional sense, often found in engineering, resilience involves statically absorbing disturbances and maintaining system performance without any changes necessary from the system. This is can be seen when a bridge withstands gusts of winds or increases in traffic and because the design incorporates some margin of error, the bridge does not have to change architecturally but simply holds up against the increased loading. However, this is a necessary but not sufficient condition for resilience. Where uncertainties are greater, systems may need to change to accommodate and can serve two purposes: to return the system to normal, or to allow a system to perform for other criteria. These are conceptualised as adapting to change and thriving for the future respectively in this work. The former was prevalent in organisational management literature where organisations have to adapt resources to recover from disasters and the latter was inspired by ecological studies where ecosystems transition between equilibria or system states. In ecology, an introduction of new species may lead to the detriment of others, yet for others, this may spawn new opportunity. This concept has given rise to the idea that resilience is not only about adversity, but also the ability of the system to evolve for new opportunities and requirements. This further parallels the idea of resilient organisations not just "surviving, but thriving".

While a substantial amount of literature was found on defining resilience and its associated attributes, there have been fewer studies on how to then endow a system with such characteristics. As such this gap in research was chosen for further study and the identified concepts were therefore mapped to engineering design strategies robustness, adaptability and flexibility respectively to understand how these characteristics may be designed into an engineering system. These were distinguished in terms of the system's response to change, system performance, and the location of the change agent. This is shown in Figure 2.16.

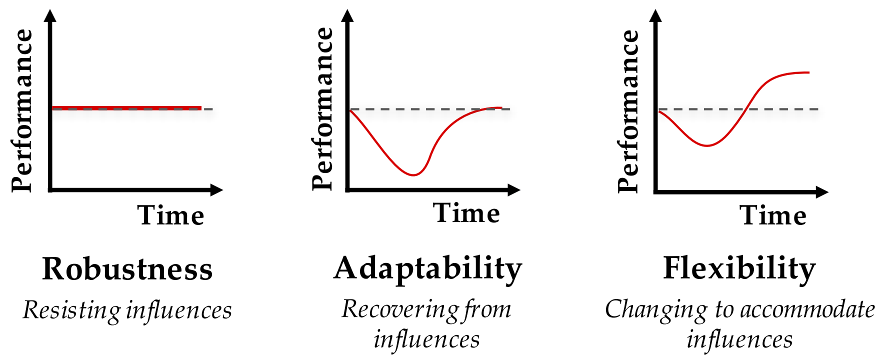


Figure 2.16. Relationship between robustness, adaptability and flexibility

Both robustness and adaptability serve to maintain the system's performance at some normal level. Robustness maintains desirable output without the need to change the system while adaptability involves some internal change agent to recover to some predefined performance. Flexibility, in contrast, allows decision makers or an external change agent to modify the system so that it can perform for new requirements.

From these properties, a definition for resilience in engineering infrastructure systems was established to ground work moving forward. A conceptual model then further discussed these three ilities in terms of uncertainty bounds. For example, for conditions that are predictable, it may be more economical to design a robust or adaptable system to handle known variances whereas for more unpredictable events, a flexible system may be more appropriate. This further introduces ideas of time as it is generally easier to predict events that are closer in time than those in the far future. From this reasoning, a system may be designed to be robust for a set of known conditions that may exist in the near future and to be flexible for unknown eventualities in the far future.

For infrastructure systems which typically have long lifecycles, there therefore needs to be a balance of robustness and flexibility. Robustness here refers to a "total robustness" of the system at deployment and takes into account both robust and adaptable strategies since the two properties serve to maintain a fixed performance envelope. More specifically, robustness refers to the performance envelope that needs to be designed into the system for deployment, while flexibility is the option to upgrade the system in the future and change the requirements when necessary. As such, it is conceptualised that every design has some robust bound and flexibility serves to transition between designs, giving it the ability to perform with new requirements. Resilience therefore involves understanding how to best traverse the solution space by finding the optimal path between designs and in doing so, ensuring the longevity of the system. The various considerations and properties of the ilities to achieve resilience are summarised in Table 2.5. While the table shows all three ilities for comprehensiveness, the most important, as discussed, are robustness and flexibility such that the aim is to understand whether the system should be designed for change after deployment.

Table 2.5. Summary of resilience properties and characteristics

Resilience Characteristic	**Engineering Design Ility**	**System Response**	**Change Agent**	**Return to Normal Performance**	**Uncertainty/ Performance Bounds**	**Timescale**
Absorbing Disturbances	Robustness	None	N/A	Yes	Fixed after deployment, predictable	Near future
Adapting to Change	Adaptability	Yes	Internal	Yes	Fixed after deployment, predictable	Near future
Thriving for the Future	Flexibility	Yes	External	No	Changeable, unpre-dictable	Far future

The final part of the literature review involved searching for resilience models which could be used to search this solution space and analyse this strategic view of resilience. Qualitative and quantitative approaches were evaluated to understand whether this had been addressed before and whether there could be a research gap. In engineering studies, resilience is often quantified by the recovery time such that both robustness and adaptability serve to return the system to a desired state while in ecology, resilience is measured by the amount of disturbance taken to change the state of the system. Organisational studies employed the use of surveys to measure resilience through some aggregate scoring of the perceived resilience factors. From this search a quantitative trade space method was found to be useful in evaluating the trade-off between multiple designs and a similar approach is suggested for further consideration.

To the author's knowledge, there has been no research in using a strategic view of resilience in engineering infrastructure systems to understand how to best traverse the solution landscape with robust and flexible strategies. The conceptual requirement for this work thus seeks to understand the trade-off between robust and flexible strategies in order to achieve resilience in engineering infrastructure systems. This provides grounding for Chapter 4 to identify quantitative approaches to address these challenges from an engineering design perspective.

Chapter 3

Methodology

The previous chapter examined resilience in a number of domains to identify the characteristics, concepts and state-of-the-art evaluation methods for resilience. Design methods were also investigated to understand how engineering infrastructure systems could exhibit a resilient response when subject to uncertainty. A conceptual model of resilience for this work was developed and research gaps were identified for further consideration. This chapter outlines how these gaps may be addressed moving forward so that there is novel contribution from this work and includes revisiting the first set of research questions as well as defining a high level research plan to guide the next phases of research. This chapter is structured in accordance with the Design Research Methodology (DRM) to outline how the thesis fits into the methodology.

Within the DRM, Blessing & Chakrabarti (2009) acknowledges that not all research projects are the same and not all phases require the same depth of study. Having conducted the literature review to understand the current research landscape in resilience, one of the seven variants of the DRM, as shown in Figure 3.1, can be chosen based on the identified research gaps. All seven types start with a review-based research clarification to refine the scope of the work. In Descriptive Study I, a review-based study is where only a literature review is conducted while a comprehensive study requires a literature review and additional work by the researcher, perhaps some preliminary modelling. This is similar in the Prescriptive Study and Descriptive Study II where an initial study only completes the first steps of evaluation in preparation for further work by other researchers.

The first four project types are noted to be more suitable for PhD projects due to time and resource constraints while latter project types are more time intensive, especially types with comprehensive evaluations, and thus are more

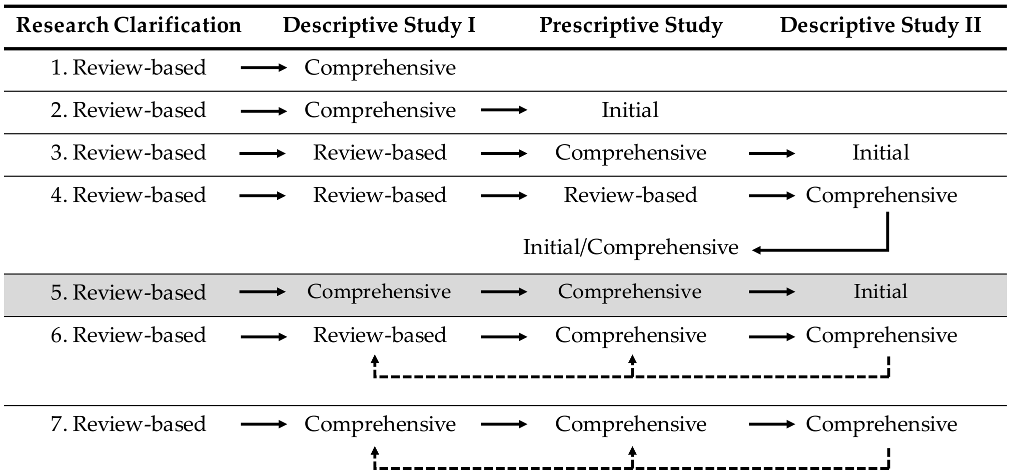


Figure 3.1. Seven types of DRM identified, adapted from Blessing & Chakrabarti (2009). The fifth type, as highlighted, is adopted in this work.

appropriate for larger research teams and projects. That said, this work follows the fifth type of DRM, as highlighted, where there is a comprehensive Descriptive I and Prescriptive Study and an initial Descriptive II study. The initial stages of Research Clarification largely involved reviewing literature and working with BT to define suitable research directions. Descriptive Study I was comprehensive due to the large scope of resilience which led to not just a literature review but further work in developing a conceptual model for resilience. Further work is necessary to build a quantitative model to assess the state-of-the-art techniques from real options theory and to provide technical requirements. This was necessary since, to the author's knowledge, literature in resilience has so far not been synthesised for infrastructure systems from an engineering design perspective. Based on the conceptual, business and technical requirements gathered in the preceding phases, a comprehensive Prescriptive Study was conducted to develop a support method which is able to assess different design strategies for resilience. However, only an initial Descriptive Study II was conducted to evaluate the research and industrial contribution of the support method with BT. Time constraints meant that further iterations and evaluations of the support method necessary to make the Descriptive Study II a comprehensive study and production ready for industry were not completed. Iterations between the earlier stages of the DRM were essential, however, in order to refine the problem definition. The remainder of this chapter serves to further detail the work done in each of the stages.

3.1 Research Clarification

The first step in the DRM involves research clarification and is typical in many projects, both in academia and in industry where the objectives, scope, requirements and outcomes are defined at the beginning of the work. Here, this has been conducted through meetings with the industrial and academic stakeholders which identified resilience in engineering infrastructure systems to be a key area of mutual interest. This led to an initial literature review to understand the broader context of resilience in various domains before narrowing the scope to the specific fields that would be investigated. From this initial review and discussion, business requirements were gathered and a hypothesis along with research questions were postulated as presented in Chapter 1. These were established to guide the comprehensive literature review in Chapter 2 and the first set of research questions can now be answered to expose research gaps that should be considered for further work. The hypothesis and first set of research questions are repeated here for convenience.

> **Hypothesis**
> Designing resilience into engineering infrastructure systems through engineering design strategies, allow such systems to better accommodate forthcoming uncertainties.

In order to address this hypothesis, the first set of research questions pertained to understanding resilience in engineering infrastructure systems and the strategies to design resilience into such systems. To continue further work, it has been important to establish the definition of resilience moving forward since resilience has found utility in many domains. As such the first research question was posed as:

RQ1 What is a useful definition of resilience for engineering infrastructure systems?

Upon reviewing the characteristics and evaluation methods from resilience literature as well as design approaches from engineering design, the definition of resilience for this work, as given in Chapter 2, is defined as:

Resilience Definition
Resilience is the system's response to uncertainty, be it risk or opportunity, through both robust and flexible strategies such that it continues to function to the fullest possible extent over time.

This reflects the findings that the sentiment of resilience is shifting to account for opportunities as well as risk which traditionally has been ubiquitous in resilience literature. Furthermore, this definition echoes the need for some trade-off between the robustness and flexibility of systems and elicited through exploring RQ2 and RQ3. The second research question addressed the engineering design properties require to enable resilience and is given as:

RQ2	What engineering design properties are required by engineering infrastructure systems to enable resilience?

Through the literature review (Section 2.1) three characteristics were found to be necessary for a system to be resilient: absorbing disturbances, adapting to change and the ability to thrive for the future. These were extracted by searching across engineering, organisational management and ecological literature. Engineering literature held a more traditional view where resilience serves to mitigate risk and adversities through redundancy as well as safety margins. Adaptability was found to be especially relevant in organisational management where resilience required the reorganisation of resources to maintain business as usual and to keep systems operational. Both of these views were prevalent throughout resilience literature. However, work in ecological studies offered an interesting alternative view where resilience is the amount of disturbance needed to make an ecosystem "flip states" or shift in equilibrium. For example, an introduction of new species or an increase in temperature from global warming may result in fluctuations of populations in an ecosystem. If this change is significant, this may lead to the extinction of some species, while others may thrive, and thus there can be a shift in equilibrium of the ecosystem. This view is being adopted in other domains and in business environments, the introduction of a new competitor may indeed lead to the demise of another. Thus resilience in this sense does not serve to maintain the status quo through redundancy or adaptation, but highlights how systems need to keep evolving by moving from equilibrium to equilibrium.

In order to incorporate these characteristics into the design of engineering infrastructure systems, the characteristics were then translated into the engineering design properties of: robustness, adaptability and flexibility respectively. Robustness came naturally given that some definitions and factors for resilience stated the need for redundancy, tolerances and margins. In this case, the system maintains performance without the need to change. Adaptability was similarly mentioned in literature but semantic challenges arose from the differentiation of adaptability and flexibility. Here, adaptability was where the system maintains performance through some changes of the system and the change agent is internal to the system. Flexibility, however, serves to move the system for new operational requirements and gives an external change agent or decision maker the ability to exercise different options in the future. These three engineering design ilities were then related in terms of uncertainty and performance to give a conceptual model and conceptual requirements.

The next stage of research clarification thus involved finding methods from resilience literature that was able to model and evaluate resilience from a strategic perspective. It is suggested that designs have initial robust bounds (incorporating robustness and adaptability) and flexibility serves to move between such bounds. There thus existed a trade-off between these two ilities which was necessary to be modelled for resilience. The third research question therefore sought methods that could be used to evaluate this view of resilience, given as:

RQ3 How can resilience in engineering infrastructure systems be modelled?

Engineering resilience is typically measured by the recovery time for the system to return to normal. Surveys were also found to measure organisational resilience through some aggregate score of the underlying factors as presented in section 2.3. However, there did not seem to be an approach that addresses this strategic view of resilience in engineering infrastructure systems found from the second research question. The conceptual requirements found that there needed a trade-off between robust and flexible strategies and thus a trade-off between how much to redundancy to allow in the system now and how much to upgrade in the future. If performance criteria does not change over time, it may be more beneficial to design a one-off robust system. On the other hand, allowing for flexibility gives room to operate given new requirements. This perspective on resilience, to the author's knowledge, has not been found in resilience research and forms the research gap to be addressed in this work. As such, this research question is only partially answered from the literature review and prompts for further search, as detailed in Chapter 4, in engineering design models which may be able to fulfil these specific needs.

3.2 Descriptive Study I

The outcome of Descriptive Study I, namely an understanding of the current state-of-the-art in resilience, feeds back to complete the Research Clarification phase and maps out the rest of the research work. This involved a more specific literature review into resilience in the domains engineering, management and ecology were reviewed to define the characteristics and properties necessary for enabling resilience in engineering infrastructure systems. Further literature in engineering design methods and engineering change management were then consulted to examine how these characteristics may be then designed into engineering systems and led to the synthesis of a conceptual model for resilience detailed in Chapter 2. While a number of models were reviewed in Chapter 2 from resilience literature, none were found to specifically address the strategic views for resilience identified in this work. Furthermore, a quantitative model was deemed valuable to generate and simulate a number of scenarios for an engineering system. Thus in order to answer RQ3, further technical requirements for the support method are derived by developing a reference model which was extended from existing models from engineering design and change management. It was identified that Real Options Theory could be suitable in addressing these requirements, especially this strategic view, and thus the Least Squares Monte-Carlo method was adapted for resilience in Chapter 4 with evaluations of the method given at the beginning of Chapter 5 to drive development of the support method.

Through Descriptive Study I, the identified research gaps led to three objectives which should be addressed in this work: 1) To develop a quantitative evaluation method for resilience in engineering infrastructure systems, 2) To understand how design strategies affect resilience in engineering infrastructure systems and 3) To providing guidance for decision makers to enable resilience in engineering infrastructure systems. The first objective follows from RQ3 where it has been identified that there needs to be a model to capture a strategic view of resilience while the latter two objectives concern gaining insights of design strategies for resilience. This is addressed in RQ4 as presented below.

RQ4 How can engineering design strategies be used to achieve resilience in engineering infrastructure systems?

Assessment of design strategies for resilience can then be conducted by applying the novel support method from RQ3 to case studies. In this thesis, two case studies are chosen to explore this: a benchmark application to a Waste-to-Energy System in Singapore and an applied case for telecommunications investment in BT to gauge industry interest. In particular, explorations of the model are taken to satisfy the business requirements in understanding how the design strategies affect the technologies that the system should have, when they should be deployed and the order of upgrade in order to achieve resilience.

This leads to the next set of research questions which evaluate the support method, given the requirements gathered earlier. The final two research questions assess whether the support method has been effective and appropriate in designing resilient engineering infrastructure systems. These questions reflect the importance of verifying that the model is technically sound and validating that the end solution meets the expectations of the stakeholders. RQ5 is given as:

RQ5 How well does the support method meet requirements for designing resilient engineering infrastructure systems?

The support method is verified against the business, conceptual and technical requirements gathered in Chapter 1, 2 and 4 respectively to ensure that the model is to specification. The final research question addresses the validity of the support method and is given as:

RQ6 How fit for purpose is the support method in designing resilient engineering infrastructure systems?

This question assesses whether resilience can actually be improved through the design strategies recommended through the model in practice and thus evaluates the usefulness of the end solution. By building a support method that fulfils requirements and is useful, guidance can be given to industry for further work. These are questions revisited in Chapter 7 to evaluate the success, impact and limitations of this work.

The work flow of the thesis is presented in Figure 3.2 and shows how the questions drive and are addressed by the respective chapters in this work. A research plan is also established to guide further work and contributions as shown in Table 3.1.

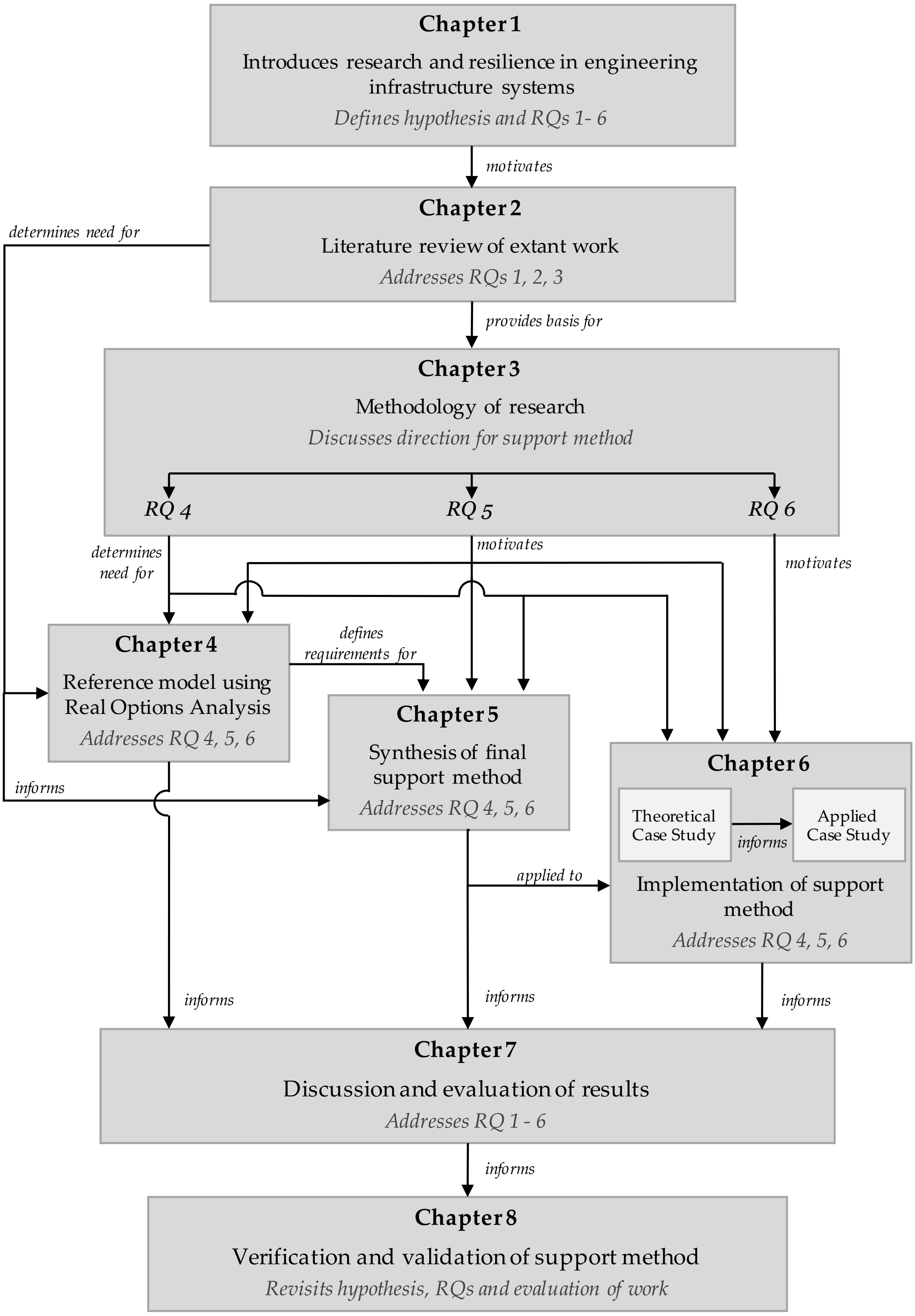


Figure 3.2. Relationship between chapters driven by research questions

Table 3.1. Research Plan for this thesis

Research Plan	
Research focus	Modelling, simulation and analysis of the impact of design strategies on resilience in engineering infrastructure systems
Research objectives	Contribute to knowledge in engineering design and: 1. To develop a quantitative evaluation method for resilience in engineering infrastructure systems 2. To understand how design strategies affect resilience in engineering infrastructure systems 3. To providing guidance for decision makers to enable resilience in engineering infrastructure systems
Relevant areas to be consulted	Modelling and simulation in engineering design Resilience (in engineering, management, ecology) Design strategies for change (robustness, adaptability, flexibility) Systems modelling Real options
Type of research	Comprehensive study of the state-of-the-art Development of the support method Theoretical and applied proof of concept through case studies
Expected areas of contribution	Resilience modelling in engineering design, decision making under uncertainty
Deliverables	Modelling approach for assessing design strategies in engineering systems Guidance for organisations

3.3 Prescriptive Study

A key part of design thinking and the DRM is determining the correct definition and framing of the problem so that the solution is not just technically sound but also useful in solving the correct problem. As such, a substantial effort has been made to elicit the challenges industries are facing and not just understand what resilience is, but how to then synthesise the appropriate solution to the research questions. To this end, business, conceptual and technical requirements from the Research Clarification and Descriptive Study I phases were brought together in the Prescriptive Study to develop a novel support model, also known as the impact model, to address the identified research gaps. This can be also shown as the Double Diamond design process as shown in Figure 3.3.

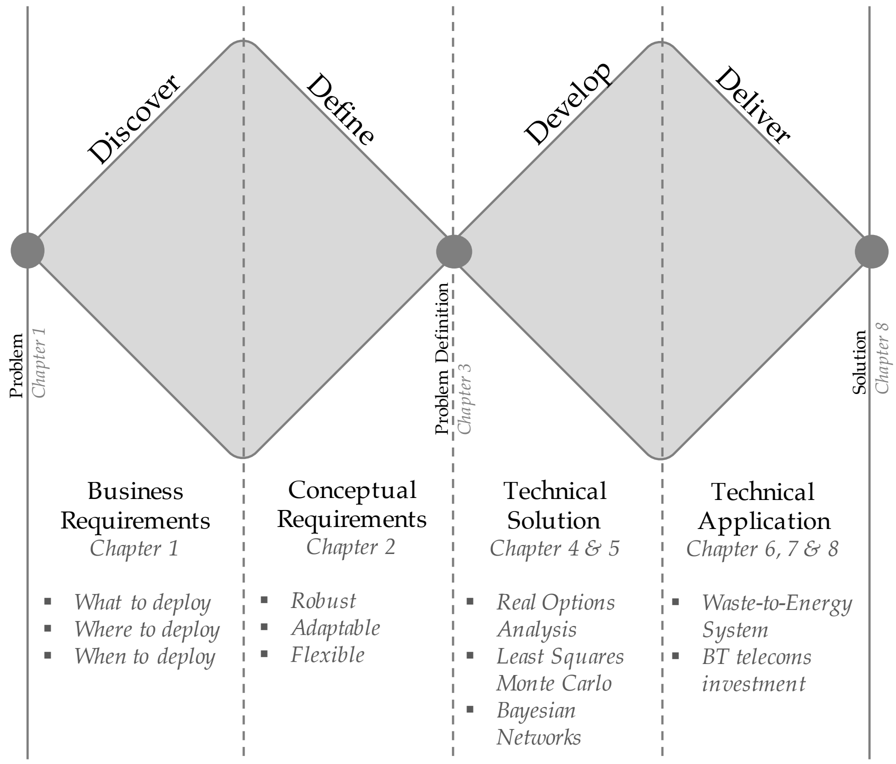


Figure 3.3. Double Diamond design process

The Double Diamond diagram illustrates how the design process combines divergent thinking, where ideas are generated and explored, as well as convergent thinking where ideas are refined and narrowed down. This happens twice: once to understand and formulate the problem and again to create the solution. Similarly, this work first involved the discovery of business needs (Chapter 1) and a search of the recent challenges in academia (Chapter 2) to explore opportunities for research. A convergent process followed the literature review to establish the definition of resilience and problem definition (Chapter 3) before diverging again to search for possible modelling solutions (Chapter 4) from engineering design. Given the full requirements from the previous phases, the research now converges by selecting a model for application (Chapter 5). Specifically, Bayesian Networks are introduced which, to the author's knowledge, has not yet been applied to real options problems and resilience. Finally, the model is evaluated through applications to case studies (Chapter 6, 7). By following such a process, it ensures that the work does not end up solving the wrong problem and a suitable support method is developed.

3.4 Descriptive Study II

The final stage of the DRM, the Descriptive Study II, serves to apply the developed support method to case studies (Chapter 6) in order to assess whether the research questions have been answered appropriately and requirements have been met (Chapter 7). As this research project aims to contribute to both academic and industry knowledge, it is crucial to also both verify and validate the support method.

The model was applied to an established Waste-to-Energy system study in Singapore to benchmark the model and then to a telecommunications case with BT to understand the reception of the model in industry. For both cases, in line with the real options paradigm, technology options were selected based on the observed characteristics and uncertainties in the problem. The first case study involved replicating an established Waste-to-Energy model but with Bayesian Networks as a proof-of-concept. When developing quantitative models, it is difficult to gauge whether results are expected and therefore by working on an existing case, it is easier to troubleshoot and gain confidence in the model. With the experience from the first study, the second case applied Bayesian Networks to BT and the problem of telecommunications investment across UK. This provided further insight on how to extract knowledge from industry experts for input into the network. The structure of the Bayesian Networks are highly subjective and eliciting the nodes, values and probabilities is an active area of research. Here, this was completed through a series of three workshops where experts were gathered across relevant domains to determine the variables of interest, dependencies and assumptions in the model. Between each workshop, models would be refined and iterated so that validation was incorporated into the process. This is further detailed in Chapter 6.

Upon applying these case studies, the support method must be verified and validated. Verification is concerned with whether the system has been built right, whereas validation assesses whether the right system has been built. In other words, verification ensures that the model has been built with rigour, is error-free and to specification, but not whether it is useful. Validation is therefore needed to check against the stakeholder requirements to confirm the model is of use.

In this study, verification was conducted by testing against an established study of a Waste-to-Energy system so that the results could be benchmarked. Validation compared the support method with the business, conceptual and technical requirements derived in first four chapters of the thesis. Furthermore, results were presented back to BT to gauge the practicality of the model to industry and obtain feedback. Future validation and success therefore constitutes applying the results and support method from this work to other research projects to prove applicability and usefulness.

3.5 Summary

This thesis itself may be seen as an engineering design process where background research is conducted and requirements gathered to design, in this case, a support method for designing resilient engineering infrastructure systems. As such, the DRM was followed and the steps taken accordingly have been elaborated upon in this chapter. The action taken in each phase of the DRM is summarised in the following table:

Table 3.2. Summary of actions taken in each phase of DRM

DRM Phase	Chapter of Thesis	Action Taken
Research Clarification	1 & 3	Met with stakeholders Defined business requirements Conducted initial literature review to determine academic challenges Defined hypothesis Defined research questions Defined research plan
Descriptive Study I	2 & 4	Met with stakeholders Conducted comprehensive literature review Defined research gap Defined conceptual requirements Developed reference model Defined technical requirements
Prescriptive Study	5	Met with stakeholders Evaluated and selected support method based on requirements Theoretical understanding of support model
Descriptive Study II	6 & 7	Met with stakeholders Applied of support method to case studies Evaluation, verification and validation of support method

Chapter 4

Exploring Modelling Methods for Resilience

A literature review was conducted in Chapter 2 to understand the characteristics of resilience and the current state-of-the-art in evaluation models from resilience literature. It was found that, while there has been substantial work in defining the concepts of resilience, there has been less work on the quantitative assessment of strategic resilience for engineering infrastructure systems. In particular, a method is needed to assess the trade-offs between robustness and flexibility so that system designs can be measured and improved. This chapter further explores methods from engineering design for resilience assessment and, more specifically, techniques are drawn from the design for flexibility as well as real options literature since they have been found to address similar challenges. A preliminary model using a Least Squares Monte Carlo approach was adapted for a telecommunications case to give a comprehensive understanding of the state-of-the-art and to gain further insight into the technical requirements for an improved resilience assessment support method.

4.1 Methods to Address the Research Gap

The literature review in Chapter 2 revealed that resilience comprised a balance between robust and flexible strategies so that uncertainties, from the operational, day-to-day fluctuations, to long-term unknowns can be addressed. Models, both qualitative and quantitative, were further examined in resilience literature to understand approaches which could be used to tackle the problem. However, engineering resilience models seemed to focus on recovery behaviour while qualitative organisational studies were unable to capture and compare a large number of designs. To the author's knowledge, there has not been any studies found in quantitatively addressing this view of strategic resilience for engineering infrastructure systems and therefore the focus of further work involves understanding the requirements for a novel assessment method for resilience.

From engineering design, a number of quantitative techniques may be used to assess robustness, adaptability and flexibility respectively. Indeed, each one of these properties are a whole field of engineering design in their own right. Since a more strategic view was needed for this work, further literature from flexibility was investigated. The field of designing for flexibility, as defined by de Neufville & Scholtes (2011) and peers at MIT, attempts to address a similar set of challenges to those for resilience and provides such a framework through engineering design and real options. Although their work does not specifically refer to the terms resilience and adaptability, the concepts behind their work, addressing both upsides and downside of uncertainty, are similar and have stemmed from the need to manage uncertainty. Crucially, there is also the recognition of addressing uncertainty in two parts of robustness and flexibility, albeit with a focus on the latter, and thus this field warrants further investigation.

The analysis for flexibility thus involves methods for understanding and evaluating uncertainty to elicit what, where and when to build mechanisms into a system. Despite the semantics, the flexibility framework is taken in a broader sense to manage uncertainty and has been chosen for the following reasons:

1. Design for flexibility recognises robustness and flexibility for the management of uncertainty (de Neufville *et al.*, 2004)
2. Design for flexibility allows systems to strategically design for and consider opportunities in the future
3. Design for flexibility considers both upside and downside of uncertainty
4. Design for flexibility allows for quantitative evaluation through real options – a similar approach was used in study by BT to evaluate the merits between small and large cabinets (Tahon *et al.*, 2013)
5. Design for flexibility sits within Engineering Design and aligns with the expertise and interests of the author's research group in the University of Cambridge

The design for flexibility from engineering design therefore forms the foundations of the support method moving forward. Borrowing from financial literature, the design for flexibility framework primarily allows system designers to exercise specific decisions at a future date to change the system depending on the circumstances. Stemming from real options literature, a flexible strategy protects the system actively by designing systems that have the option, but not obligation, to be exercised in the future (Trigeorgis, 1996). This idea has proven to be valuable in the design of engineering systems. For example, the Health Care Service Corporation (HCSC) building in Chicago used phasing which is an example of flexibility and adds extra capacity at a later date to manage uncertainty. The original building was constructed with the strength to add an extra 27 floors when capacity was reached. This option was eventually exercised at a time where there was better information regarding demand (Guma *et al.*, 2009). In this example, the initial number of floors constructed represents a robust core which does not change. The flexibility option concerns the addition of the new floors which does not necessarily need to be undertaken if conditions are not favourable. By having both of these properties, the downside risk of not utilising full capacity is mitigated and the upside of having more demand can be accommodated. This is similar to the conceptual model developed in Chapter 2 where each design has some initial robustness and flexibility serves to upgrade the system for some new requirements when necessary. While studies in flexibility have highlighted the benefits of such an approach, from a resilience perspective, there should be some balance between the advantages of robustness and flexibility. For example, if the requirements are to change very little over time, a simple robust option may be more economical and therefore there must exist some threshold point where it is better to go for each respective strategy.

Here, the real options paradigm, which is associated with the design for flexibility, is chosen to assess resilience as it can be used to evaluate which technology investments, or options, to implement in a system under uncertainty. Each different available technology investment, such as different telecommunication network line types, can be thought as a real option which allows for alternative choices to be deployed in the future. Putting this in terms of the conceptual model discussed in Chapter 2, each real option can be thought of as a design with a robust bound and some performance characteristic. Flexibility thus evaluates each design, or real option, to understand when to switch between designs. In the case of a telecommunications system, an organisation may have invested research into different types of network fibres and this research into future technologies allows a decision maker in the organisation the ability, but not obligation, to deploy these different technologies in the system. Similarly, the Ponte 25 de Abril suspension bridge over the Tagus River had the real option to add a secondary railroad deck that was implemented only when there was sufficient demand.

Real options was originally derived from financial options literature and used as a method to quantify the value flexibility when investing under uncertainty. Formally, real options give the right but not obligation, to buy or sell some real, physical asset or take some action at a future date (Trigeorgis, 1996). Furthermore, real options evaluation considers designs for a range of future possibilities instead of a fixed projection on performance as per traditional engineering analysis and therefore aims to reduce the likelihood of leaving value untapped or incurring major losses. Some examples of the early work in applying real options to evaluate flexible investment strategies focus on natural resources such as mining (Brennan & Schwartz, 1985), renewable energy (Santos *et al.*, 2014) as well as risk management (Huchzermeier & Loch, 2001). For the assessment of real options, the investment strategies can be categorised using the 7S framework by Antikarov & Copeland (2001). This defines seven category types: scale up, scale down, scope up, scope down, switch up, switch down as well as study and wait. The first options, scaling up or scaling down the project, involves expansion or reduction of the project respectively. For a telecommunications networks, this could be to roll out the network further or slow down the rollout phase. In the extreme case, scaling down the project could also be where the entire project is abandoned. Scope up and scope down options allow management to change product portfolio requirements. This change in management requirements can potentially in turn affect how the project is scaled or switched. The switch up and down option allows for a change in technology with switch up giving rise to better products but usually incurring some extra cost. The final option, study and wait, simply does not exercise an option and the decision makers wait for more favourable conditions.

In terms of resilience, the robust case can be modelled as the benchmark case where no real options or technologies are implemented and there is no change in the system. This could be the option to study and wait indefinitely. The adaptable case can be seen to be analogous to switch options which would allow for reversible switching between technologies whereas in the flexible case, this switch would be irreversible and could be closer to the scope up/down or scale up/down options. Compound options deals with situations where more options may be added on top of options, such as multiple flexible switches. This is summarised in the Table 4.1.

Table 4.1. Addressing system lifecycle properties through different option types

System Lifecycle Property	Option Type	Change Type
Robustness	None	None
Adaptability	Switch Option	Reversible
Flexibility	Scale Up/Down, Scope Up/Down Option	Irreversible

This further allows the trade-off between robust and flexible options to be evaluated through real options so that the optimal transition between designs can be assessed. Resilience would therefore involve finding the decision strategies which optimise the return on the system, measured by the system's economic lifecycle value, through robust and flexible options. While much literature has measured resilience in terms of recovery and uncertainty, by mapping resilience onto financial returns, this becomes more tangible for industry and can be used to support business cases for investment. Furthermore, for large complex organisations, there will be inevitability a multitude of key performance indicators which makes it hard to aggregate performance into some score for resilience. All parts and decisions of the organisation, however, can be mapped to some financial value. This financial metric further allows for comparison across industries.

The real options paradigm has demonstrated to address similar challenges as those identified in Chapter 2 and is therefore adopted in this work to understand the different options that should be designed into a system so that resilience may be achieved. The next subsection further explores the methods and techniques to evaluate real options and how these may then be used to assess resilience.

4.2 Designing for Flexibility and the Real Options Paradigm

Having identified that the design for flexibility could be a good fit to evaluate resilience, the field is explored broadly to understand the framework and how it can be used to evaluate design options. A taxonomy, as shown in Figure 4.1, of flexibility has been developed by Cardin (2014), based on similar framework by de Neufville & Scholtes (2011). It provides a comprehensive view of the design for flexibility and used in a number of flexibility analyses (Anvarifar *et al.*, 2016; Engel & Reich, 2015; Haddad *et al.*, 2014). This will be used to structure the examination of the state-of-the-art in this domain. The diagram shows a five-phase process to design a system for flexibility. The first phase at the top of the cycle involves establishing the benchmark design to be analysed and gives some baseline for new designs to be compared against. This initial design can be a new design or taken from an existing system. The second phase concerns identifying the uncertainties that may affect the system performance in the future. The following phase identifies flexible design options to address these uncertainties and the final phase in the cycle evaluates the trade-offs between the different solutions. The new design with embedded flexibility can be further iterated through this process. In the centre of diagram, connected to all other phases, lies process management which prompts to the need for collaboration with stakeholders throughout the whole process. Each phase in this diagram is now explored further in the following subsections to identify the potential contributions of this work.

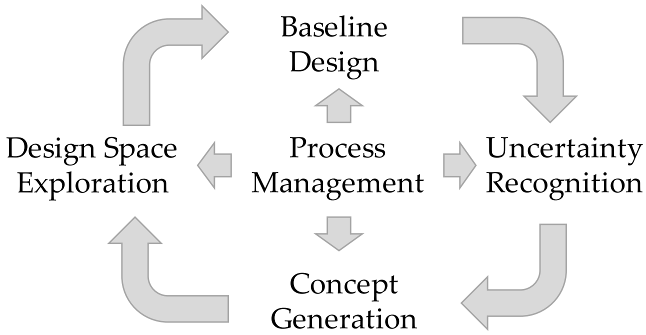


Figure 4.1. Design for Flexibility taxonomy, adapted from Cardin (2014)

4.2.1 Baseline Design

This phase involves establishing a baseline design for which to embed flexibility and can take the form of an existing system or a new design. It is beyond the scope of this work to evaluate all conceptual design methods since a system already exists with the industrial partner, BT, and thus only a few procedures will be mentioned here for reference. For new designs, conceptual methods as described by Pahl & Beitz (2013) may be employed. This involves identifying the problem through abstraction and establishing the functions and principles of the solution. The concept is developed through embodiment design where the ideas are conformed to technical and economic criteria resulting in a detailed design. Another approach, proposed by Suh (1995), is axiomatic design where matrices are used to map customer needs to functional requirements, design parameters and process variables. Using these matrices, a flow diagram for system architecture is constructed. Bayesian networks have also been used by Moullec *et al.* (2012) to generate product architectures (Moullec *et al.*, 2013). The Bayesian network is a probabilistic graphical model that represents a set of variables and their joint probability distributions. Uncertainties are integrated through probability functions and viable system architectures are explored. These procedures are used to aid the conceptual design process and further information on the design process may be found from "Design Process Improvement" by Clarkson & Eckert (2010).

After establishing the baseline design, either new or extant, the design is evaluated to set a benchmark so that the improvements gained from adding flexibility may be assessed. Since the framework is cyclical, the methods to evaluate flexibility in this initial step are the same as those in the final step of the cycle and will be discussed further in the design space exploration phase.

4.2.2 Uncertainty Recognition

This phase aids the designers in understanding how uncertainties affect the system lifecycle performance. Traditionally, the analysis of uncertainty results in a fixed figure or projection. However, these estimates are unlikely to be accurate, especially when predicting for the long-term, and instead, a range of scenarios must be considered (de Neufville & Scholtes, 2011). By designing for a range of possibilities, a compromise needs to be made between designing for all possible outcomes – an impractical task – and designing for too specific a result. The "flaw of averages" demonstrates the asymmetries in investment and the dangers of relying on average forecasts where it is assumed that the under-predictions will balance out the over-predictions (Savage, 2002). For example, a manufacturing plant can be designed for a certain production capacity based on a likely forecast. There is an asymmetric risk where it is easy for the plant to not fill capacity, but much harder to increase capacity if necessary without considerable cost. In other words, an over-prediction may not be realisable, but an under-prediction is definitely feasible. Thus, having one fixed average projection is not representative of the risks involved in a real project. This prompts to the need for flexibility so that the design can accommodate a range of scenarios should the need arise. That said, if the range of predicted possibilities is sufficiently narrow, a robust design may also suffice. Nevertheless, in both cases, a prediction of uncertainty of some sort is needed to anchor the design.

Usually uncertainty takes the form of demand, but other sources should also be considered so that more possibilities may be assessed. A classification of the sources of uncertainty by de Weck *et al.* (2007) is shown in Figure 4.2. The uncertainty can be broadly classified as either endogenous, coming from within the system and shown by the dashed box, or exogenous, coming from external sources. Often, endogenous uncertainties are well understood by companies and it is the exogenous factors that are difficult to predict.

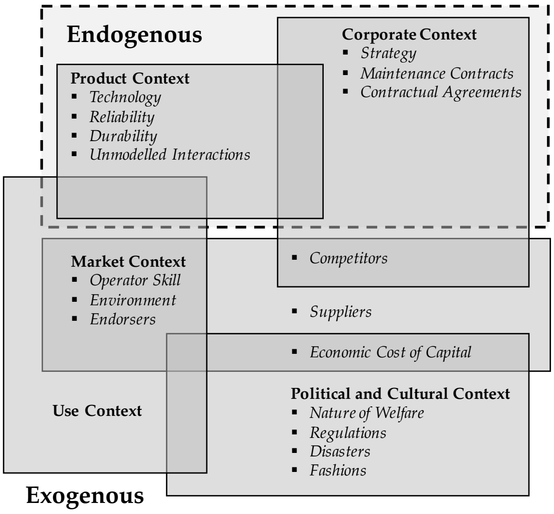


Figure 4.2. Classification of uncertainties, adapted from de Weck *et al.* (2007)

There is further classification of five types: product, corporate, use, market and political and cultural. The first two types are endogenous with the remaining being exogenous uncertainties. Product context focuses on the technical risks and the interaction of system components. These include the risk of failure through the system lifecycle or impact of reusing a design for another purpose (Eckert *et al.*, 2004). In a corporate context, the uncertainties come from business processes such as altering resource allocation and product strategy. The requirements for a product also often change through the design process leading to rework and cost. This is reflected in the Rule of Ten which suggests that a change in a later phase is ten times more expensive than a change in a previous phase (Boehm, 1984; Fricke *et al.*, 2000). The uncertainty in use context refers to how the system is used in operation and whether it is used appropriately by the end-user. This differs from re-use since in this case, as it refers to how the end-product is utilised whereas re-use refers to the design process and thus use context is an exogenous uncertainty. Markets typically carry a large amount of uncertainty and an inappropriate forecast in market demand could very well end in bankruptcy (de Weck *et al.*, 2004). Furthermore, competition is difficult to predict and can change the market dynamics quickly. Looking more broadly, the market is in turn affected by political and cultural influences. This could take the form of a change in legislation or change in customer preferences.

A variety of models exist to model uncertainty and, although the assumptions may not always be correct, it is important to give a foundation for the design of the system. These methods include using statistical techniques, simulations and machine learning. Since these methods are entire fields of research in their own right, only techniques that have been used in the design for flexibility are discussed here. Methods used in flexibility include linear regression, diffusion models, binomial lattice, decision trees and scenario planning.

Linear regression is a statistical technique which has been used extensively in industry and one of the oldest topics in mathematical statistics. Regression analysis is used to discover relationships between dependent and independent variables. Simple linear regression specifically considers the linear relation between one dependent and one independent variable, thus having the form $y = \beta_0 + \beta_1 x + \varepsilon$, where y is the dependent variable, β_0 the y intercept, β_1 the gradient, x is the independent variable and ε is the random error. The values for β_0 and β_1 are found through fitting the line to data. Other regression types include multiple regression which assumes that there are more than one independent variable and non-linear regression is used where the function is not linear. By fitting a linear, or otherwise, function to data, predictions can be made on new independent variables. This technique is used by de Neufville & Scholtes (2011) to forecast demand for a maternity hospital which needed to build an extension following an increased number of births delivered in the hospital. A linear regression was fitted to data for the annual number of births and this is done repeatedly at different points in time for 10 year periods. A prediction into the future therefore takes a Monte-Carlo approach by applying linear regression and introducing a random error to produce a range of future probabilities.

Diffusion models are used for modelling stochastic processes which are characterised by the Markovian property, where future states only depend on the present state and not on the preceding states (Ikeda & Shinzo, 2014). Geometric Brownian motion (GBM) is a type of diffusion model which is commonly used in finance to predict stock prices and is applied by de Weck *et al.* (2004) to model the evolution of the market for the Iridium satellites. GBM is a continuous-time stochastic process in which the logarithm of the randomly varying quantity follows a Brownian motion, or a Wiener process, with drift (Ross, 2014b). This follows the form,

$$\frac{\Delta S}{S} = \mu \Delta t + \sigma \varepsilon \sqrt{\Delta t} \tag{4.1}$$

where S is some stochastic variable of interest, μ is the mean trend over time, Δt is the discretised time step, σ is the volatility, or spread of demand, and ε represents a random variable with normal distribution. This can be used with Monte Carlo simulation to give a range of future probabilities. However, this can be computationally expensive if many time steps are needed.

In the case that intermediate steps are not critical and an estimate is needed with many time steps, a lattice model may be more appropriate. Binomial lattices comprise a tree structure and represent a discretised form of the Black-Scholes equation (Black & Scholes, 1973) and as such, it is often used for financial options pricing. This method assumes that a variable can only either increase, with probability p, or decrease with probability $1 - p$ for some interval of time (Cox *et al.*, 1979) and is illustrated in Figure 4.3.

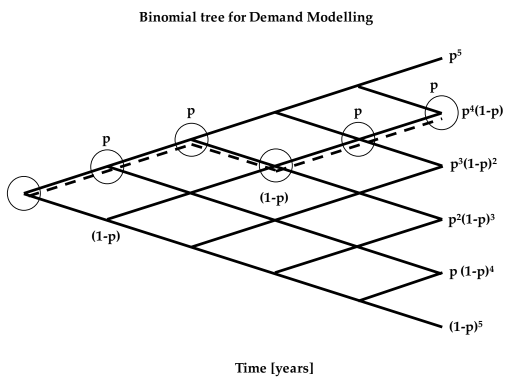


Figure 4.3. Binomial Lattice Illustration, adapted from (de Weck *et al.*, 2004)

The total probability of a scenario occurring, P, highlighted by the dashed path, may be found from,

$$P(i) = p^k (1 - p)^{k-1} \tag{4.2}$$

where k is the number of time periods in the model. The probability and value of the variables may be found at each node from the following equations,

$$u = e^{\sigma \sqrt{\Delta t}}\,, \quad d = \frac{1}{u}\,, \quad p = \frac{e^{u \Delta t} - d}{u - d} \tag{4.3}$$

where u is the factor with which S, the quantity of interest, will increase, and d is the factor with which S will decrease. The variables σ and Δt are volatility and discretised time step respectively (Hull, 2012) and is shown in Figure 4.4. This method gives a set of possible scenarios and the associated probabilities. Due to the nature of the binomial lattice, this method avoids the costly evaluation of infinite scenarios as with modelling GBM but is limited when analysing more than one source of uncertainty (Antikarov & Copeland, 2001).

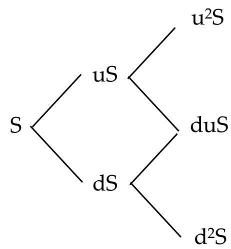


Figure 4.4. Calculation of probabilities, adapted from (de Weck *et al.*, 2004)

While these models are useful to understand the evolution of uncertainty, they are limited by relying heavily on having data and information on probability distributions (Cardin, 2014). A less data-dependent method is scenario planning which attempts to define a finite set of scenarios that could occur and thus prompting decision makers to consider changes that would otherwise be ignored (Shoemaker, 1995). Shoemaker gives a ten step collaborative process for scenario planning as follows:

1. Define the scope
2. Identify the major stakeholders
3. Identify basic trends
4. Identify key uncertainties
5. Construct initial scenario themes
6. Check for consistency and plausibility
7. Develop learning scenarios
8. Identify research needs
9. Develop quantitative models
10. Evolve toward decision scenarios

Each final scenario is then given a weighted probability or equal likelihood of occurring. This process may be complemented by the Delphi Method, "a method for structuring a group communication process", to add richness and expert information (Linstone & Turoff, 1976). However, as a consequence of gaining data through collaboration, the methods are subjective and will depend on the experts experience and knowledge. That said, it should be noted that any model, even the "objective" quantitative models, have limitations and present a certain perspective of the world. Nevertheless, the process of making such model can be useful to prompt discussion.

A number of methods have been explored in this subsection to evaluate uncertainty and to predict a range of future possibilities. These are necessary for the next phase to ensure these uncertainties are appropriately managed through design solutions.

4.2.3 Concept Generation

In this phase, designers identify concepts to tackle the uncertainties defined in the previous step. Each concept may be further classified as a strategy or an enabler. The former deals with the management decisions concerning the system and the latter refers to the actual component that is designed into the system. Both are necessary and interdependent in this phase. de Neufville *et al.* (2004) also refers to these as real "on" options and real "in" options respectively for engineering design. These are so named since strategic concepts often treats the system as a black box with analysis conducted "on" the system whereas for enablers, the design is implemented "in" the system.

Real "on" Options

Real options have emerged from financial options theory to evaluate "real" physical investment decisions. An option "gives the right, with no obligation" to take an action at a future time (Trigeorgis, 1996). The use of real options allow for the consideration and evaluation of flexibility in investments which were not fully captured by the traditional discount-cash-flow (DCF) approaches. These evaluation procedures will be discussed in the next section. A list of common strategies for flexibility, collated by the seminal work of Trigeorgis (1996), is presented below as a checklist for designers to consider.

1. Option to defer investment until more favourable conditions arise
2. Option to stage or phase the deployment strategically
3. Option to alter operating scale by increasing or decreasing output production
4. Option to abandon a project and resell assets at salvage value
5. Option to switch output/inputs *i.e.* change product or sourcing
6. Option to grow *e.g.* expand infrastructure, invest in R&D
7. A mixture of the above

For example, the option to phase deployment has been explored by de Weck *et al.* (2004) to analyse the failure of the Iridium satellite project which ended in bankruptcy. It was found that a phased deployment, instead of deploying immediately at full capacity, could have saved up to 20% in cost. It should be noted, however, that this does not mean it could have necessarily avoided bankruptcy through phasing. These options have been further applied to the design process. Mikaelian *et al.* (2011a,b) proposed an Integrated Real-Options Framework to identify where these "types" and "mechanisms" for real options could be embedded in the system. Types and mechanisms are defined similarly to strategies and enablers respectively as previously discussed. These were then mapped to enterprise architecture and UAV design, as part of different case studies, to identify the most appropriate options in different circumstances. Cardin *et al.* (2013) devised a method for designers to consider flexibility in the design process. A short lecture on flexibility was presented to participants in order to explore the effects of explicit training. Furthermore, brainstorming and prompting were also investigated for concept generation. It was found that explicit training and prompting were useful in helping designers improve the system lifecycle performance through flexibility. These techniques made the designers more aware of the value of flexibility and how to enable flexibility in design.

Real "in" Options

At the component level, real "in" options focus on the technical mechanisms of the system that enable flexibility. Examples of such mechanisms can be drawn from literature. Fricke & Schulz (2005) suggests the basic principles of ideality/simplicity, independence and modularity are needed for flexibility.

Ideality aims at reducing system complexity and architects the system so that it consists only of useful functions. This may take the form of small, simple units with a minimised number of interfaces. Independence aims at minimising the impact of changing design parameters. Suh (1995) distinguishes three degrees of independence, which are defined as coupled, decoupled, and uncoupled. Modularity architects the system so that system functions are clustered into modules while minimising the coupling between modules. As such there is loose coupling among but strong cohesion within modules. Modularity thus supports the reuse of elements and allows for exchanging or adapting modules. Furthermore, the following extending principles were also suggested: integrability, autonomy, scalability and redundancy. Integrability applies generic, common interfaces for compatibility and interoperability while autonomy provides basic functionality necessary to ensure independence from the system. Scalability allows units to combine or parameters to upsize and downsize easily and redundancy enables fault-tolerance. de Neufville & Scholtes (2011) also suggests the use of modular design, and further proposes platform design and shell design for flexibility. Platform design uses a common platform which becomes the basis of many other designs. This is has been employed in the automobile sector, for example, where different styles may be designed on top of a common base and wheel train. Shell design creates extra capacity for some undesignated use and allows for a response to some future, unknown need. For example, in a hospital, extra space may be built with no immediate purpose, but with recognition that the space will be needed at some point. This may be seen as form of redundancy to make the design more robust.

These principles can be designed into a system upon identifying the components that are most likely to change and be impacted from uncertainties. The components that are most susceptible to change may be identified using the Design Structure Matrix (DSM) which illustrates the dependencies in a system. This was first introduced by Steward to represent design tasks as a sequence of interactions through a square matrix (Steward, 1981). An example of the DSM is shown in Figure 4.5. This gives a binary matrix representation of system interrelations and elements that are off-diagonal signify a dependency between elements. Reading across a row indicates the outputs while reading down a column shows input to the element. For example, in Figure 4.5, element B provides output to elements A, C, D, F, H, and I, and it receives inputs from elements C, D, F, and H. Such dependencies have been mapped using the DSM in a variety of domains and thus give rise to many variants of the DSM including component based/architecture DSM, organisation DSM, activity-based DSM and parameter-based DSM (Browning, 2001).

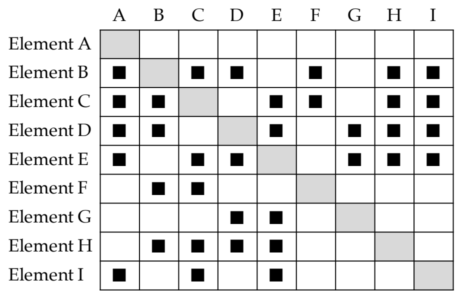


Figure 4.5. Design Structure Matrix, adapted from (Steward, 1981)

Furthermore, variants of the DSM can be used to find the impacts of and to predict change. The Change Prediction Method (CPM), for example, populates probabilities into each of the elements of the matrix (Clarkson *et al.*, 2004). Specifically, change relationships are calculated from a combination of likelihood and impact to a system. The former is defined as "the average probability that a change in the design of one sub-system will lead to a design change in another by propagation across their common interface" and the latter is defined as "the average proportion of the design work that will need to be redone". These probabilities are often derived from expert opinion and history of previous design changes. Indirect dependencies may also be accounted for by considering the probabilities of the dependent elements. The risk is then found from the product of the likelihood and impact probability matrices which is illustrated below:

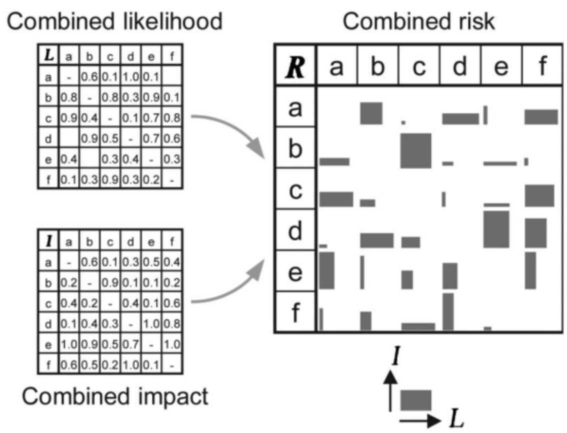


Figure 4.6. Change Prediction Method, adapted from (Clarkson *et al.*, 2004)

The risk is thus represented by a square with height and width equal to impact and likelihood respectively. An area with high risk, or a large squares show components which are susceptible to change and rework. A risk plot can also be drawn which shows the risk of all components in one diagram as shown in Figure 4.7. This plots the components on the same plot for comparison and as illustrated, the components with the highest risk lie in the top right of the diagram.

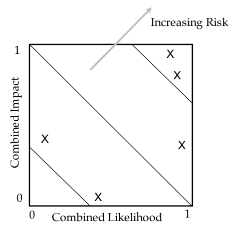


Figure 4.7. Risk plot from Change Prediction Method, adapted from (Clarkson *et al.*, 2004)

Suh *et al.* (2007) used a similar approach to identify potential candidates for embedding flexibility in a vehicle platform. It was suggested that components that are multipliers, those which impact more components when changed, are prime candidates for embedding flexibility. Despite a higher initial investment to implement flexibility, it led to significantly lower switching costs when the vehicle design changed. The conclusion of embedding flexibility where there are multipliers has also been echoed, amongst other results, by Giffin *et al.* (2009) who studied a large data set containing over 41,500 change requests generated during the design of a complex sensor system.

The sensitivity DSM (sDSM) was developed by Yassine & Falkenburg (1999) where the elements are populated by the partial derivative of the outputs of elements. Similarly, to the CPM, this aimed to represent the interactions of the system more accurately. This was used by Kalligero (2006) to find design variables that are most sensitive to changes in design and functional requirements. These were taken as candidate areas to embed flexibility and applied in offshore oil platform design. The engineering system matrix (ESM) extends a technical engineering DSM by including social components, for example, teams and organisations (Bartolomei *et al.*, 2012). This was developed into the engineering system multiple domain matrix (ES-MDM) and used to identify candidate flexibilities in unmanned miniaturised air vehicle (MAV) design. Mikaelian *et al.* (2011b) extended the DSM and multiple-domain matrix (MDM) framework to form the logical multiple domain matrix (Logical-MDM) which supports the representation of flexibility, optionability and realisability. Optionability is where a mechanism enables types of options, whereas realisability is the ability to enable a specific given type of real option. This was applied to UAV design.

Bayesian networks have also been used to map dependencies in a system and applied in the design for flexibility (Junfei, 2012; Lee & Hong, 2015). Bayesian Networks are probabilistic models that represent relationships between variables of interest through a directed acyclic graph as shown in Figure 4.8 (Ghahramani, 1998).

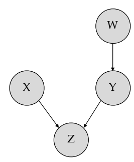


Figure 4.8. Bayesian Network Illustration of Nodes and Arcs, adapted from (Ghahramani, 1998)

Each variable is represented by a node in the network and directed edges are drawn to show a direct dependency between variables. The dependency is quantified by conditional probability, calculated through Bayes' Theorem,

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{4.4}$$

where A and B are some events, $P(A)$ is the probability of A occurring and $P(A|B)$ is the probability of A given B is true. This is mathematically developed further to compute the joint probability distribution for the whole network, allowing inference of unknown elements. Bayesian Networks have also been used in learning where probabilities are learned from data (Heckerman, 1998). A Bayesian Network was used by Hu and Cardin (2012) to calculate probabilities and thus risk in system elements in a Waste-to-Energy system. As with the other methods, the elements with the highest risk were then identified as potential candidates for flexibility.

Qualitatively, flexible designs can also be found by considering the design variables individually. de Weck *et al.* (2004) used a five variable design vector to design the deployment of a satellite constellation. From the initial design vector, two design variables, the altitude and elevation angle of the satellites were deemed to be flexible. This allowed system decision makers to change the number of satellites deployed and thus reconfigure the constellation based on demand. This approach was taken similarly by Wang (2005) for hydropower dams.

Methods to identify flexibility strategies and enablers have been outlined in this section. The different options now need to be evaluated to find the most appropriate design in each scenario. Techniques for evaluating this are shown in the next subsection.

4.2.4 Design Space Exploration

In this phase, the designers explore the design space to find the most valuable solutions. Here, the methods are categorised as either a financial or design evaluation, reflecting the differences in real "on" options and real "in" options respectively.

Financial Evaluation

The basis of real "on" options evolved from financial options theory. The simplest financial options are "calls" and "puts". The first type of option allows the right, but not obligation, to buy stock at some specified future time. The second type allows the right, but not obligation to sell stock at some specified future time. For example, a stock may be priced at \$2.40 today and a call option gives the right, but not obligation to buy the stock in a week for \$2.50. For this analysis, it is assumed that there are only two options: the stock has to go up to \$3.00 or down to \$2.00. It is assumed there are no possible intermediate values such as \$2.10, \$2.15 *etc.* If the stock price increases to \$3.00 in an upside scenario, the stock worth \$3.00 can be bought for \$2.50, making \$0.50 profit. If the stock price decreases to \$2.00, the stock can still be bought for \$2.50; However, there is no obligation to lose \$0.50 and the option is not exercised (de Neufville & Scholtes, 2011). Conceptually, the real option to increase the number of lanes on a motorway is akin to a call option on demand. That is, if the demand increases, the option can be exercised. If not, then there is no obligation to take the option.

The nature of options theory is naturally suited to tree models. One such form is decision trees where each node in the tree represents some decision or in this case real option and the branches represent the consequences of decisions. Analysis starts from the final stage of the tree that maximises expected lifecycle performance. This is computed backwards until the initial stage is reached and the overall lifecycle performance of the system is calculated. Babajide *et al.* (2009) applied this for the design of an oil platform and adding flexibility was found to increase overall expected value for 7%.

Binomial lattices are another form of tree model and have been briefly discussed previously. These are similar to the decision analysis method but strictly have two options at each node. A limitation of the binomial lattice method is the assumption of path independence which assumes lattice nodes are allowed to recombine. That is, this assumes that a downside followed by upside scenario is the same as an upside followed by a downside scenario. This may not hold true for engineering systems. While analysis with decision trees can support more options at each node compared to the binomial lattice, it can make it more complicated to compute and program.

Due care must be taken so that financial options theory is not applied directly to real options without thought. These are for a variety of reasons including: real assets are usually unique while financial assets are widely replicated; options may be valid for many years in real assets, but only valid for a few months in financial options; options are not well defined in real assets while in financial assets characteristics are defined. This makes traditional Discounted Cash Flow (DCF) and Net Present Value (NPV) evaluations more intuitive and attractive. These techniques may then be applied with a Monte Carlo simulation to simulate a range of uncertainties and flexibilities. DCF essentially views a project as a series of cash flows and considers how the time value of money affects these values. That is, money now is more valuable than in the future, usually taken into account through discount rates also known as interest rates. This is accounted for through the equations:

$$\begin{aligned} \text{Money}_{\text{future}} &= \text{Money}_{\text{now}}(1+r) \\ \text{Money}_{\text{now}} &= \text{Money}_{\text{future}}/(1+r) \end{aligned}$$

where r is the interest rate. This allows money in the future to be discounted to the present value. The NPV is therefore the sum of present values of incoming and outgoing cash flows over a period of time (Hillier *et al.*, 2013). This has been used by de Neufville & Scholtes (2011) to quantify the value of flexibility of expanding capacity for a parking garage as uncertain demand increases. The NPVs were calculated for scenarios with differing numbers of garage levels and demands to give a distribution of outcomes.

Design Configuration Evaluation

This subsection outlines work that searches, selects and evaluates the appropriateness of the design mechanisms. The field of decision-making addresses the process of making choices and may be used to explore the process of selecting between different designs. This has been developed by Simon (1959) to incorporate economics to psychology theory in order to explore rational choices and how individuals make decisions in an organisational context (Simon, 1955). Hazelrigg (1998) proposed Decision-Based Design for making decisions and selecting design configurations in environments characterised by ambiguity, uncertainty and risk. Olewnik *et al.* (2004; 2006) extended this to consider flexibility in engineering systems through decision making. In particular, this work concluded with the need to improve search techniques in order to find the best combination of adaptable and/or robust variables. The need arises since the cost of adding adaptability may not outweigh the added value of flexibility generated.

Ross (2006) developed the Multi-Attribute Tradespace Exploration (MATE) framework to explore the design space and various ilities. This, although consisting of 48 steps, can be abstracted to 3 high level stages: identifying the needs of the system, variations to the design parameters, evaluating the lifecycle cost of alternate designs. The most valuable designs per cost are found from Pareto fronts and trade spaces are used to represent transitions from one design state to another. Richards (2009) extended the framework to investigate survivability of space systems and allows the identification of survivable systems. A trade space analysis was suggested to be conducted through a workshop organised by Spero *et al.* (2014). However, the workshop concludes with issues of uncertainty propagation, subjective data, high-dimensional spaces, static and flat visualisations, combinatorial what-if scenarios, feature identification, and retention of data throughout a lifecycle have not been sufficiently addressed. These and other gaps partially exist because there appears to be interchangeability in the lexicon of related terms such as trade-off study, optimisation, alternative analysis, and value-focused thinking.

Screening methods may be used to quickly compare and evaluate through many design alternatives. More sophisticated models are commonplace in industry, but in order to search through possible thousands of designs, simplicity reduces computation time. These can by categorised into three types: bottom-up, simulators and top-down (de Neufville & Scholtes, 2011). Bottom up models focus on a higher level of granularity and thus more detailed operations view of a system whereas top-down models are concerned with the overall interactions between major components of a system. Simulators, on the other hand treat the system as a black box and aims to replicate the inputs and outputs through statistics. Lin used screening methods for petroleum exploration projects (Lin, 2008) while Wang studied hydroelectric dam design in China (Wang & de Neufville, 2005). Genetic algorithms were also used to find optimum flexible solutions for oil platforms (Hassan & de Neufville, 2006) and in maritime domain protection systems (Buurman *et al.*, 2009). Further models of organisations may be found from Sterman's book (2000).

Design catalogues may be used where it is not desirable to reduce model fidelity. Thus to reduce the computation time, only a small subset of designs that collectively perform reasonably well over a range of possible scenarios are analysed. This was applied to public infrastructure, real estate, and mining (Cardin & de Neufville, 2013; Cardin *et al.*, 2008).

4.2.5 Process Management

This phase is central to all the others and aims to better facilitate the process of instilling flexibility in organisations. It allows engagement of stakeholders so that all phases can be carried out effectively and managed appropriately. This phase may be difficult as it requires inputs from many stakeholders and thus makes interactions complex within an organisation. While this thesis focuses on "enabling resilience", it focuses more on the technical aspects rather than the process of rolling out resilience thinking into the organisation and so, less emphasis is put on this stage.

Since engineering systems are usually complex, they involve a large organisation for support. However, this may lead to a "silo" culture where teams do not share information effectively. This has also been identified as a source of problems for resilience (Lee *et al.*, 2013; McManus, 2008). This inhibits the implementation of new tasks, concepts and processes. As a result, even if designers need to implement flexibility, decision-makers may not think of it as a feasible feature or vice-versa. A lack of communication may also mean that the managers do not know that the flexibility is even embedded into the design and thus flexibility is lost. This was the case for a parking garage expansion given by de Neufville and Scholtes (2011). Option games have been also developed by Smit and Trigeorgis (2009) through integrating real options and game theory principles. This was applied to Schiphol airport to assess whether it was more beneficial to grow at the current location or partake in a strategic alliance. Simulation gaming provides interactive environments where participants learn by taking actions and by experiencing their effects through feedback mechanisms that are deliberately built into and around the game (Mayer, 2009). This was used by Sterman (1989) to assess individuals who were to manage a simulated inventory distribution system which concluded in finding several "misperceptions of feedback". Such games can help stakeholders understand the mechanics of the system so that in a real-case scenario, the appropriate action is taken (Gibson & Tarrant, 2010).

4.3 Preliminary Model for Resilience Analysis

The previous subsection explored the design for flexibility structured through a taxonomy developed by Cardin (2014) to understand how resilience maybe be analysed. Although the framework as a whole is valuable, the contribution sought by this work is in evaluating the optimal transition between designs and in understanding the balance between robust and flexible strategies. This work therefore fits within the design space evaluation phase of the cycle which may be assessed through real "in" options to study the design of the components for flexibility or real "on" options which focuses on the managerial strategy of such options. Since the aim is to understand the transition between designs, evaluation from real "on" options is deemed more appropriate and it is assumed that technology option designs already exist such that the task is to differentiate the best deployment strategy. Furthermore, the industrial sponsor is interested in which technology options to deploy over time and already has expertise on how to integrate the components into the system, giving support for additional investigation into real "on" option assessment. Indeed, there has been previous studies by BT which have used real "on" options analysis to evaluate the deployment strategy of small and large cabinets (Tahon *et al.*, 2013). Other examples of real options applied to telecommunications can be found in work by D'Halluin *et al.* (2002) and Kridel *et al.* (1993).

A preliminary model is now developed using real options to give further insight into the limitations of this approach as well as opportunities for further work. Since real options has stemmed from financial options, the methods to value real options also follow from financial options. These methods include the Black Scholes equation, binomial lattices and Monte Carlo analysis. The Black Scholes equation is one of the most important models for financial options valuation and was developed in 1973 to price European options (Black & Scholes, 1973). This pioneering formula subsequently earned a Nobel Prize in Economic Sciences in 1997. However, the formula is typically used to price European options which can only be exercised at the specific end date only. This works in finance, but for real options, where investments are on physical assets, there usually is not this restriction where the investment must be made on a specific date. For this reason, American options, whereby investments can be made at any date, are more appropriate. American options are often modelled using dynamic programming techniques such as finite difference methods, lattice methods or Monte Carlo simulations. Finite difference methods where the stock price is modelled using differential equations are difficult to implement for more complex cases with multiple variables of interest and suffer from the curse of dimensionality. Lattice methods, typically binomial or trinomial, comprise a tree structure and assumes, in the binomial case, that the variable can only either increase, with probability p, or decrease with probability, $p-1$, for some interval of time (Cox *et al.*, 1979). Lattice methods have been used widely for pricing financial options and, by discretising the problem, avoids the costly evaluation of infinite scenarios which is associated with Monte Carlo techniques. These are, however, limited when analysing more than one source of uncertainty. Monte Carlo methods involve random sampling and are commonly used for multi-dimensional problems in a number of domains such as modelling fluids, structures in physical problems as well as business uncertainty and risk. While more computationally expensive, this allows for more comprehensive analysis of uncertainty in further analysis for resilience and taken for further study.

Of the number of Monte Carlo approaches taken to evaluate real options problems, the most promising technique is the seminal work presented by Longstaff & Schwartz (2001) using a Least Squares Monte Carlo (LSM) approach. This technique is adapted for a telecommunications case and demand on the network is simulated through geometric Brownian motion with the payoff being discounted backwards through time to find the optimal exercise policy. Resilience can be investigated by comparing different options and varying volatility in the demand. Furthermore, a robust case is used to serve as a benchmark and compared to the flexible case, where there is an irreversible change of technology. The flexible case therefore represents upgrades in technology and it is assumed, in this study, that the flexible options are mutually exclusive so that only one option, or upgrade, may be exercised at any one time.

The contribution of the LSM technique lies in using least squares regression to determine the continuation value of the Bellman equation of an option and therefore allows the optimal execution policy of the investment to be found. The general outline of this technique is first given before being applied to a telecommunications example in the next subsection. The general problem is formulated by assuming that some stochastic input(s) affects the system and therefore influences investment decisions. For a telecommunications network, this could be the demand or usage of the network. The stochastic input of demand, X_{t_n}, on time step, t_n, with N time steps, can be modelled through a geometric Brownian motion given by,

$$X_{tn} = X_{t_0} e^{(r - \sigma^2/2)t + \sigma W(t))} \tag{4.5}$$

where X_{t_0} is the initial value of input X at $t = 0$, r is the growth trend of the demand or drift, σ is volatility, and $W(t)$ is standard Brownian motion. This is then used to calculate some payoff, $\pi(X_{t_n})$, which can be understood as the telecoms operator profit from the demand. Let $F(t_n, X_{t_n})$ be the value of the option between time, t and at the option maturity, and the problem then becomes an optimisation of the value of the option, $F(t_n, X_{t_n})$ in the following equation,

$$F(t_n, X_{t_n}) = \max_{\tau \epsilon \tau(t_n, T)} \left\{ \overset{*}{\underset{t_n}{\mathbb{E}}} \left[e^{-r(\tau - t_n)} \pi(\tau, X_\tau) \right] \right\} \tag{4.6}$$

where τ is the optimal stopping time in $[t_n, T]$. That is, the optimisation finds the optimal time, τ, to invest in the appropriate real option and gives the value of the investment. The LSM uses a backward dynamic programming algorithm for this optimisation to approximate the expected value. Dynamic programming solves optimisation problems by dividing the computation into smaller sub-problems. In essence, the algorithm starts at the final time, T, and marches backwards through the time steps until $t = 0$. At each time step, the algorithm compares whether it is better to exercise the option at the current time step, or hold the option with the expectation that the value of the option will increase. This is computed by calculating the continuation value of the function at each time step and comparing with the value at the current time step. The continuation value is found from

$$\Phi(t_n, X_{t_n}) = \overset{*}{\underset{t_n}{\mathbb{E}}} \left[\sum_{i=n+1}^{N} e^{-r(t_i - t_n)} \pi(t_n, t_i, \tau) \right]. \tag{4.7}$$

This is estimated using least squares regression where the payoff π, is projected onto a set of basis functions. The Laguerre polynomials are used here since other studies (Gustafsson, 2015) have found them to give appropriate results. The first four functions are defined as:

$$L_0(x) = 1 \qquad L_1(x) = 1 - x$$

$$L_2(x) = \tfrac{1}{2}(x^2 - 4x + 2) \qquad L_3(x) = \tfrac{1}{6}(-x^3 + 9x^2 - 18x + 6)$$

The estimated continuation value can therefore be calculated through least squares,

$$\widehat{\Phi}^J(t_n, X_{t_n}) = \sum_{j=0}^{J} \widehat{\Phi}^J(t_n) L_J(t_n, X_{t_n}). \tag{4.8}$$

This is applied recursively to the following decision rule at each time step, giving

$$\text{if} \qquad \Phi(t_n, X_{t_n}) \leq \pi(t_n, X_{t_n}) \qquad \text{then} \qquad \tau = t_n.$$

The optimisation of the value function, $F(t_n, X_{t_n})$, can therefore be written as

$$F(t_n, X_{t_n}) = \max\left\{\pi(t_n, X_{t_n}), \Phi(t_n, X_{t_n})\right\}. \tag{4.9}$$

The optimal stopping time is found by recursive application of the decision rule from final time T. If the expression is true, the stopping time is updated so that $\tau = t_n$. When the computation reaches $t_n = 0$ and all the optimal stopping times are determined, the value of the American option is estimated by averaging the values for each simulated path, ω

$$F(0, x) = \frac{1}{K} \sum_{\omega=1}^{K} e^{-r\tau(\omega)} \pi(\tau(\omega), X_{\tau(\omega)}(\omega))). \tag{4.10}$$

This forms the basic LSM method for American options valuation. In applying this for resilience, each option or available investment is valued using the LSM method with the robust case being the baseline case where there is no upgrade in technology. The other options are also evaluated similarly and represent flexible options or technology upgrades.

4.3.1 Preliminary Application to Telecommunications

The LSM method, as outlined from real options literature, is now applied for a telecommunications case. The parameters used for the equations and simulations presented in this section are for illustrative purposes only and do not represent actual data from the telecommunications company. First, the stochastic input, assumed to follow a geometric Brownian motion, is generated to simulate the demand on the telecommunications network. The drift or trend of demand, r, and volatility, σ, are fixed for the simulated period. Typical simulated paths are illustrated in Figure 4.9.

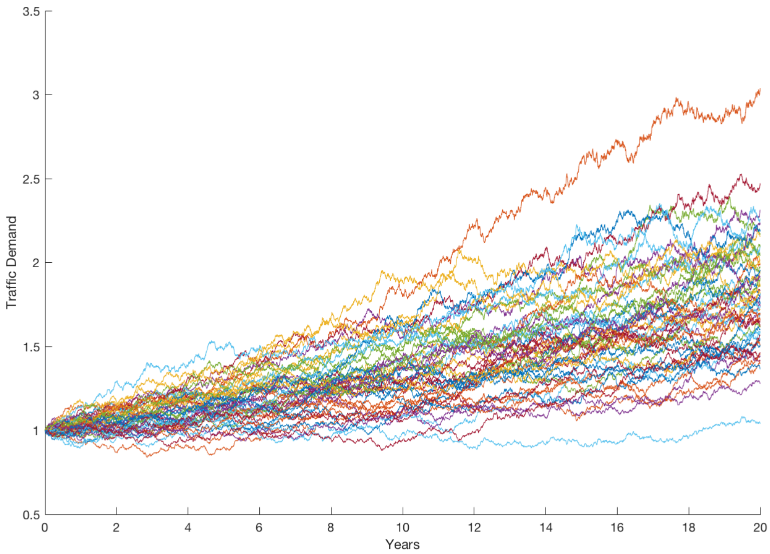


Figure 4.9. Illustration of demand simulation with $X_{t_0} = 1, r = 0.05, \sigma = 0.1$

The payoff, $\pi(t)$, for each technology is a function of demand and, for telecommunications models, it is assumed that the payoff or profits generated from demand can be derived from the customer's satisfaction. Here, Enderle and Lagrange's model (2003) for customer satisfaction is employed and is given by

$$H_t(X_t, C) = e^{-\beta/Q_t(X_t,C)}, \tag{4.11}$$

where H_t is customer satisfaction, C is the capacity of a cell of the network, β is chosen such that $\beta = \log(2) \cdot q_{1/2}$, where $q_{1/2}$ is the throughput value ensuring a satisfaction of 50%, and Q_t is the quality of service calculated from $C - X_t$. The customer satisfaction is then multiplied by some transfer price, δ, so that the operator receives some payoff. Following Morlot, Elayoubi and Redon's work (2012), the net profit may therefore be calculated from,

$$\pi(t) = \delta X_t e^{-\beta/(C-X_t)} \qquad \text{if} \quad X_t < C$$
$$\pi(t) = 0 \qquad \text{otherwise}$$

Illustrative parameters used for further analysis are shown in Table 4.2 and the resulting plots are shown in Figure 4.10 where each curve represents a different technology or option type.

Table 4.2. Option parameters with the Least Squares Monte Carlo method

Option	δ	$q_{\frac{1}{2}}$	C
1	1	0.5	2
2	3	0.5	2
3	3	5	4
4	1	0.5	4

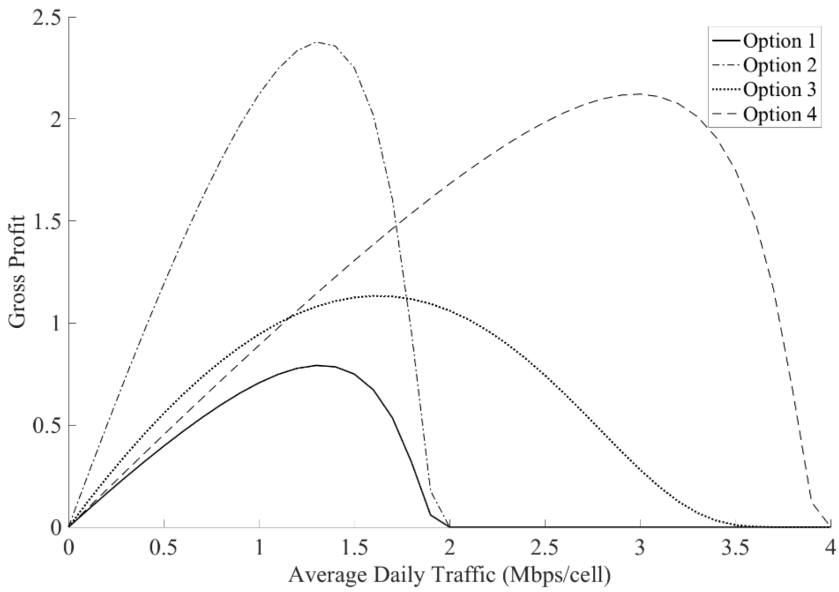


Figure 4.10. Payoff curve plots

The robust case (Option 1), shown by the solid line, represents the benchmark option. The other options/curves represent other technology investments and therefore flexibility to upgrade the system. All options are valued to obtain $F(t_n, X_{t_n})$ and compared under varying drift and volatilities to assess for resilience. The four options as presented in Table 4.2 are first assessed for response to varying drift. This is shown in Figure 4.11 and volatility is fixed to 0.01 day$^{-1/2}$.

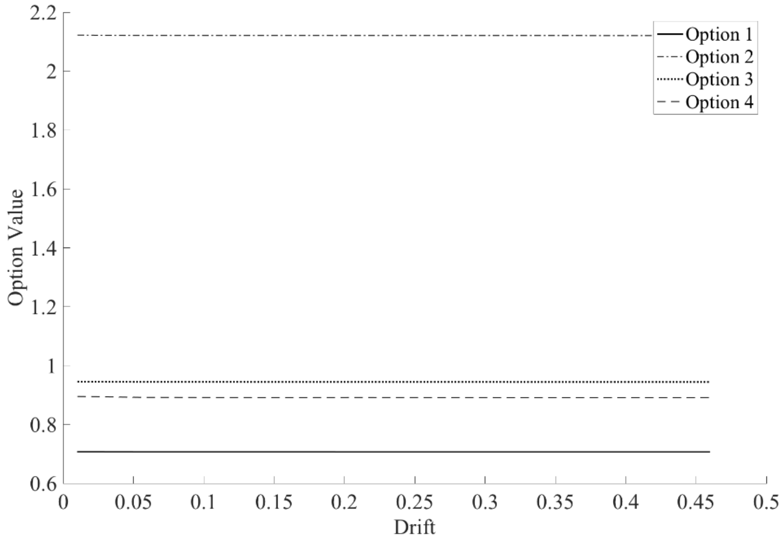


Figure 4.11. Option response to varying drift

The value of all the options remains relatively constant with standard deviations of 0.001, 0.004, 0.002 and 0.015 for options 1 to 4 respectively. The lowest valued option, Option 1, is as expected, the robust option. This is done similarly for varying volatility and fixing drift to 0.1 per day. The resulting plot is shown in Figure 4.12.

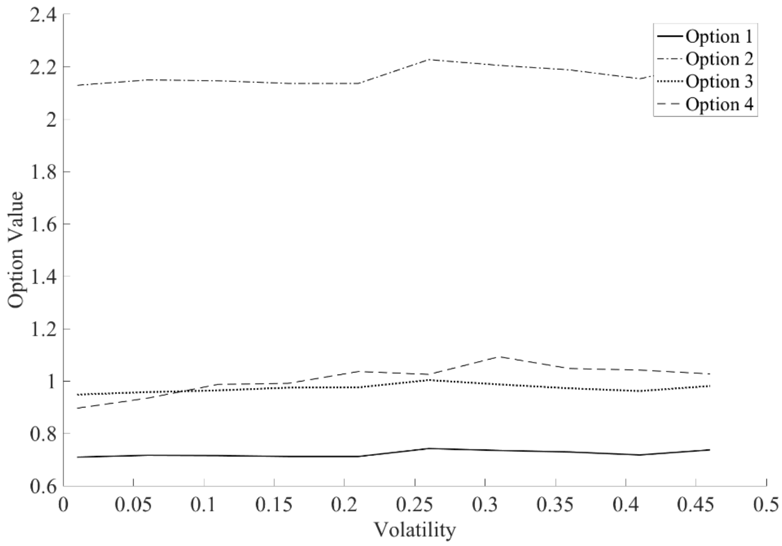


Figure 4.12. Options response to varying volatility

The standard deviations for Options 1 to 4 are 0.008, 0.024, 0.011 and 0.067. The options values give higher standard deviations when changing volatility compared to when varying drift. It can also be seen that there is a slight upward trend particularly for Option 4. The results show that the smallest curve, the robust option, has the least value for all drift and volatilities as expected. Option 2, with the highest peak gives the highest values in Figures 4.11 and 4.12. However, while Option 4 has the largest integral area under the curve, when comparing drift and at low volatilities, it does not return the highest payoff. This may be attributed to the demand at $X_{t_0} = 1$ so that for low drift and low volatility, the demand does not change significantly above or below 1. By looking at the payoff curve where the demand or average daily traffic is 1, it is clear that Option 4 returns less than the other options apart from the robust option. For this reason, at demands close to 1, Option 4, while having the largest payoff curve, is not the most valuable. When volatility is varied, however, the value of Option 4 displays a slight upward trend and is valued higher than Option 3 at higher volatilities. This is due to a larger proportion of the curve being captured and at higher demands Option 4 indeed gives a higher return than Option 3. This also gives reason as to why volatility changes affect the model more than changes in drift. A higher volatility gives a higher spread of demand and as such, more of the curve is covered. The drift would have to be relatively higher to give the same spread in demand.

The preliminary results have demonstrated that different options may be valued using the LSM method. The valuation of each option allows uncertainty in the form of volatility and drift to be captured so that a decision maker can assess which option to choose given a projected risk. The further challenge lies in using this model in decision making and understanding how to choose the options in transition such that resilience may be achieved.

4.4 Limitations of Model

The Least Squares Monte Carlo approach was applied to a telecommunications example to understand how the state-of-the-art in real options could be used to evaluate resilience. The valuation was based on each option having some payoff curve and the size and shape of which could be relatable to the robust bounds as discussed in the conceptual model in Chapter 2. However, the payoff curve so far only captures the capacity before mapping this to some revenue. In reality, especially for infrastructure systems, many more uncertainties exist and the relationships of all of these would be difficult to relate to payoff in this way. From de Neufville *et al.* (2004), failure need not only stem from technology but also from human factors. As such, the LSM would provide value in financial options where uncertainties pertain to stock price but may be need to be improved to incorporate further uncertainties.

The robust curve has also been assumed to be the smallest curve, with flexibility being some extension of the robust payoff. Further work should investigate other output curves where flexibility may not be just an enlargement of the existing curve, but a shift along the axes. This is important for resilience since there needs to be some transition between designs. If each option is only a larger payoff curve, the flexible strategy would be favoured in all studies. Instead, there should be sufficient difference between the designs and in multiple dimensions to be explored.

While different options can be valued through the LSM approach, there is opportunity for further work in developing a support method for resilience in engineering infrastructure systems. The limitations of the preliminary work prompts further a technical requirement for the support method and is given as:

Technical Requirement

- To consider a holistic view of engineering infrastructure systems by capturing more types/number of uncertainties acting on the system

This would involve establishing some method where uncertainties can be captured across the system and does not necessarily have to be mapped to drift and volatility, which can be hard to measure. Furthermore, the dependencies between parts of the system must be accounted for due to the complex nature of infrastructure systems.

4.5 Summary

The chapter further explores methods from flexibility literature to address the strategic view of resilience identified in Chapter 2. From previous it was found that in order to achieve resilience, there needed a balance between robustness and flexibility as well as recognising both positive and negative uncertainties. The work in designing for flexibility was found to be useful in that it met these criteria for resilience and stemmed from the need to manage uncertainty in engineering design. A taxonomy developed by Cardin (2014) was used to structure further examination of methods which could be appropriate for this work and is composed of five phases: baseline design, uncertainty recognition, concept generation, design space exploration and process management. The real options paradigm associated with the design for flexibility, views each separate design as an option which could be exercised in the future and was found to be useful for this work moving forward. Thus, real options theory, borrowing techniques from finance, was used to build a preliminary model to understand how this could be adapted for resilience analysis.

In particular, the Least Squares Monte Carlo method was used to value each option with the robust case being the benchmark and representing no change in the system. Flexibility is where there can be upgrades to the system and thus other options or investments are also valued. This is applied to an illustrative telecommunications case and the usefulness of the model is assessed. The results show that uncertainty, captured as drift and volatility, in the model can affect the option value and therefore can aid in assessing which technology option or investment to choose to for future planning. However, the model relied on payoff curves to calculate revenue and thus the value of each option focused primarily on these payoff curves. This may not be suitable for all types of uncertainties and it may be difficult to capture the complexities needed for a large-scale infrastructure system using this method. Furthermore, the transition between designs need to be better modelled and the payoff curves need to be better differentiated. Thus, the technical requirements sought a quantitative method to evaluate between options whilst capturing a larger set and type of uncertainties. These technical requirements are used for the novel support method to be developed for further work moving forward in the next chapter.

Chapter 5

Development of Support Method for Infrastructure Resilience

The previous chapters have thus far served to gather requirements for the support method to be developed for this work: business requirements were discussed in Chapter 1, conceptual requirements were established through the literature review in Chapter 2 and Chapter 4 derived further technical requirements. These are revisited here to summarise and synthesise the support model given the various insights gained from the previous work before being applied to case studies in the next chapter. In particular, a high-level discussion of the implementation and evolution of the support method is given here, compared to the detailed results in the next chapter, to show the various design considerations of the final framework in bridging from the research gap to the novel contribution. More specifically, Bayesian Networks are proposed to be implemented into the support method and details of the underlying theory, how these were then built for the case studies and assumptions that were made are discussed. Exactly how this is then applied and the results of analysis are presented in the next chapter.

5.1 Requirements for Novel Support Method

The first challenge in developing the support method involved finding research areas of mutual interest between the stakeholders. Being sponsored by industry, this topic would ideally be of both industrial and academic value. A number of meetings were arranged with BT to understand the ideas that industry were interested in and these were then mapped onto engineering design concepts and techniques which could be used to address such challenges. The unrolling of new technology through the Next Generation Access (NGA) scheme was suggested as a case study to leverage the academic group's expertise in change management and the term resilience was incorporated to address how the network should be designed such that it can strategically upgrade with a view of potential risks and opportunities. The key areas of interest for stakeholder groups are shown in the following figure.

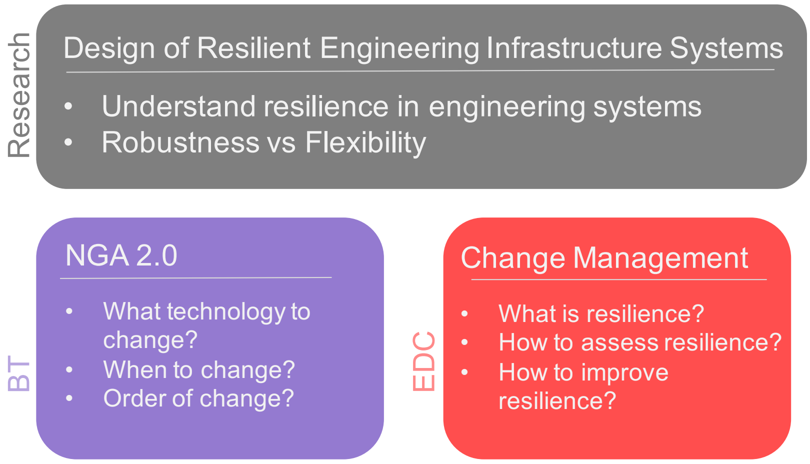


Figure 5.1. Key areas of interest between stakeholder groups

For BT, the main question and requirements that should be addressed are related to the deployment of the technology options and more specifically:

Business Requirements

- To understand what technology options are most appropriate for different areas of Cambridgeshire
- To understand when technology options should be changed for different areas of Cambridgeshire
- To understand the optimal order of change for each of the technologies options for different areas of Cambridgeshire

The first question revolves around the fact that different areas of the UK, known in BT as geotypes, have particular characteristics. London, say, would have different properties compared to Cambridge and thus the investment decisions of which technologies to roll out in each area may also be different. Following on from this, when these technologies should be installed is important given the long-term investment horizon of BT. Finally, BT has a portfolio of technologies that can be utilised for various situations, all with their own properties. As such, it may be the case that not all technologies need to be used and there may be some optimal transition between select technologies.

From an academic perspective, the author's research group expertise lies in change management in engineering design and as such, the management of the transition between these designs and technologies have been of interest. The precise definition of resilience, however, had to be uncovered since it has become a buzzword in industry and thus literature from engineering, organisational management and ecology were further consulted in Chapter 2 to define exactly what needed to be designed. The interpretation of resilience here has been taken from the perspective of change management and engineering design which therefore forms a specific approach to the problem. A more formal set of initial research questions, compared to those shown in Figure 5.1, were determined to lead the literature review and establish conceptual requirements. This led to a set of three characteristics being distilled from literature: absorbing disturbances, adapting to change and thriving for the future. These were then mapped to the engineering design system ilities of robustness, adaptability and flexibility respectively before exploring the suitability of each of these design types with respect to change and uncertainty. A conceptual model was constructed to illustrate the effects of these properties on performance bounds of a system and it is suggested that resilience involves the effective transition between designs. Specifically, each design has some performance envelope, which may include robustness and adaptability strategies, at the point of deployment, or some "initial robustness". These are used to maintain some level of performance that has been specified at the conceptual design stage. Flexibility then allows the design to be evolved and is therefore necessary if the performance criteria needs to be changed. Due to the long lifecycles involved with infrastructure systems, there clearly needs to be some balance between robustness to meet the demands in the near future, and flexibility to address longer term unknowns. The key conceptual requirement thus becomes:

Conceptual Requirement

- To understand the trade-off between robustness and flexibility in designing resilient engineering infrastructure systems

Pragmatically, for BT's case, this becomes the understanding of the amount of internet bandwidth to provide to customers now and the cost-benefit of deferring investment to the future. Relating to the conceptual model, each of BT's technology options therefore have some robust margin and, while adaptability can be taken to be some software solution of automatic re-routing of traffic, there is some total robustness of what the technology can handle once deployed. Flexibility then concerns the upgrade process between the different technologies. Resilience is thus the maximisation of the system's lifecycle value under both positive and negative uncertainty, through a balance of robustness and flexibility. To understand these trade-offs, evaluation of resilience is necessary and further resilience literature was examined to understand the state-of-the-art for assessment so that the designs can be compared. It was found that there has been a number of qualitative studies in understanding the factors that influences resilience but less work in quantitative assessment for the strategic view of resilience used in this work. Most of the existing quantitative models have focused on the traditional view of resilience where resilience is measured by recovery time and there has been no work, that the author is aware of, relating resilience to a quantitative strategic future-proofing view offered here in this work. Chapter 4 therefore further explored techniques from the design for flexibility which stemmed from the need to manage uncertainty and addressed similar challenges. The real options paradigm was then selected for further investigation and the Least-Squares Monte Carlo (LSM) approach was adapted for a telecommunications example to understand the merits and limitations of these methods. This preliminary case study was used to derive further technical requirements for this work. Whilst satisfying the business requirements, the main limitation of the LSM method with respect to this work was that it focuses heavily on a financial payoff which, although useful for financial options, may be difficult to use in capturing the range of uncertainties in infrastructure systems. There was a need to capture a more holistic view of the system since resilience would need to incorporate multiple varying sources of uncertainty and the technical requirement is therefore:

Technical Requirement

- To consider a holistic view of engineering infrastructure systems by capturing more types/number of uncertainties acting on the system

With these requirements defined, a novel support method is proposed by incorporating Bayesian Networks with the real options paradigm and flexibility framework. This is discussed further in the next subsection.

5.2 Integrating Bayesian Networks into the Flexibility Framework

It has so far been identified that approaches from the real options paradigm, which are also linked to work in flexibility, could be useful in resilience analysis and addresses similar challenges to this work. The LSM method was taken to represent the state-of-the-art in real options evaluation and adapted for a telecommunications example to understand the opportunities for further work and potential areas of contribution. While the LSM method was found to be able to compare technology options, the primarily financial focus made it difficult to capture a holistic view of the system and the interdependencies in terms of payoff. Upon further consideration of literature, Bayesian Networks were suggested to be implemented as an approach to choose between different design options in terms of the decision rules taken by organisations as opposed to purely financial calculations. That is, the current real options techniques chose investments based on financial considerations and Bayesian Networks differ by being able to classify which technology to deploy depending on a larger set of decisions, not necessarily financial, thus meeting business and technical requirements. The investments, however, based on these decisions are mapped to Net Present Values, a financial metric, to give a tangible basis for assessing different designs and in order to understand the conceptual requirement of understanding the balance between robustness and flexibility. Bayesian Networks have also found utility in many fields and in engineering design they have been employed to synthesise product architectures (Moullec *et al.*, 2012) as well as analysing the impacts of change in order to identify where to install flexible components (Hu & Cardin, 2015). To the author's knowledge, Bayesian Networks have not been used to choose between design options in real options evaluations for resilience. Further advantages of the Bayesian Network are (Heckerman, 1998; Nielsen & Jensen, 2009):

- Bayesian Networks can compute inference between qualitative and quantitative variables allowing for a wide range of uncertainties to be captured
- Bayesian Networks can be used for causal (explaining away), diagnostic and predictive reasoning
- Bayesian Networks can compute inference from cause to effect as well as effect to cause

- Bayesian Networks do not need all variables in the network to be observed and can combine multiple sources of information to arrive at strong hypotheses through a rigorous mathematical probabilistic foundation

- Bayesian Networks form an intuitive decision support tool for industry – their graphical structure are interpreted relatively easily compared to black box models such as neural networks

- Bayesian Networks can exploit prior domain knowledge which is particularly useful when working with industry partners

- Bayesian Networks have a more compact representation compared to decision trees

The main limitation of Bayesian Networks, however, is the subjective nature of the graph structure and design methodology. There is no standard approach to building Bayesian Networks and is based on the knowledge of domain experts. No approach, however, is without limitation and Bayesian Networks are integrated into the flexibility framework for resilience analysis with evaluations on this approach given in Chapter 7. The underlying theory of Bayesian Networks are discussed in the next subsection before detailing some considerations of applying this framework in case studies for resilience assessment.

5.3 Bayesian Network Theory

Bayesian Networks are probabilistic graphical methods which represent variables and their conditional dependencies through directed acyclic graphs (DAG) (Nielsen & Jensen, 2009). Nodes are used to represent variables with a finite set of mutually exclusive states and a set of edges show the conditional dependencies between variables. Their ability to be used for causal reasoning and inference have led to applications in many domains, including: medical diagnosis (Flores *et al.*, 2011), risk analysis (Weber *et al.*, 2012) , decision support (Wiegerinck *et al.*, 2013), prediction and classification (Heckerman, 1998). Bayesian Networks capture the joint probability distribution of the set of variables such that given some observation or belief, inference is used to update the probability distribution of the other variables via Bayes' Theorem (Pearl, 2009) given as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{5.1}$$

where A and B are some events, $P(A)$ is the probability of A occurring and $P(A|B)$ is the probability of A given B is true. This is derived from the fundamental rule of probability where,

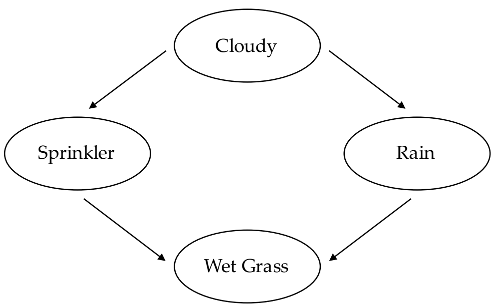
$$P(A \cap B) = P(B)P(A|B). \tag{5.2}$$

That is, the probability of A intersect B occurring can be calculated by knowing the probability of B and also probability of A given B. Similarly,

$$P(B \cap A) = P(A)P(B|A). \tag{5.3}$$

Since $P(A \cap B) = P(B \cap A)$, equating and rearranging the equations yields Bayes' rule. This is demonstrated through the canonical sprinkler example (Gales, 2005; Murphy, 1998) which is shown in Figure 5.2.

P(C-F)	P(C-T)
0.5	0.5



C	P(S-F)	P(S-T)
F	0.5	0.5
T	0.9	0.1

C	P(R-F)	P(R-T)
F	0.8	0.2
T	0.2	0.8

S	R	P(W-F)	P(W-T)
F	F	1.0	0.0
T	F	0.1	0.9
F	T	0.1	0.9
T	T	0.01	0.99

Figure 5.2. Sprinkler example

There are four nodes, Cloudy, Sprinkler, Rain and Wet Grass, each with their own conditional probability tables (CPTS). The arrows represent edges to show dependencies between variables. For example, Sprinkler depends on its parent node, Cloudy. Looking at the bottom right of the CPT of the Sprinkler node, the probability of the Sprinkler being True, given that Cloudy is True is 0.1. Likewise, the probability of Wet Grass being True, given that Sprinkler and Rain is True is 0.99. Questions on the model may now be asked such as: "What is the probability the grass is wet (W_T) given that it is Cloudy (C_T)?" This can be calculated from Bayes' Rule through:

$$
\begin{aligned}
P(W_T|C_T) &= \frac{P(C_T|W_T)P(W_T)}{P(C_T)} = \frac{P(W_T, C_T)}{P(C_T)} \\
P(W_T, C_T) &= \sum_S \sum_R P(W_T, S, R, C_T) \\
&= \sum_S \sum_R P(W_T|S, R)P(S|C_T)P(R|C_T)P(C_T)
\end{aligned}
$$

Through marginalisation, there is a summation over the variables S and R being True or False. $P(C_T)$ is cancelled from numerator and denominator giving:

$$
\begin{aligned}
P(W_T|C_T) = \quad & P(W_T|S_T, R_T)P(S_T|C_T)P(R_T|C_T)+ \\
& P(W_T|S_F, R_T)P(S_F|C_T)P(R_T|C_T)+ \\
& P(W_T|S_T, R_F)P(S_T|C_T)P(R_F|C_T)+ \\
& P(W_T|S_F, R_F)P(S_F|C_T)P(R_F|C_T) \\
P(W_T|C_T) = \quad & 0.99 \times 0.1 \times 0.8 + \\
& 0.90 \times 0.9 \times 0.8 + \\
& 0.90 \times 0.1 \times 0.2 + \\
& 0.00 \times 0.9 \times 0.2 \\
P(W_T|C_T) = \quad & \underline{0.7452}
\end{aligned}
$$

This can be done similarly across the network to find probabilities of the other variables. Exact and approximate algorithms have been developed for this purpose but is outside the scope of this work since the aim of this work is not to improve Bayesian Network development. Furthermore, the structure of Bayesian Networks as well as the CPTs can be learned from historical data. However, there has been insufficient data for this and instead, this work leverages the Bayesian Network's ability to use expert knowledge to obtain the structure and

CPTs. Interested readers are directed to Koller & Friedman (2009); Nielsen & Jensen (2009); Russell & Norvig (2016) for much greater elaboration.

The diagnostic properties of Bayesian Networks can be further demonstrated through the canonical example of the "Chest Clinic" as shown in Figure 5.3. This is drawn in Netica (Norsys Software Corp, 2018), a Bayesian Network building software which is used further in this work. The boxes represent variables and the bars represent the probability for each state. In this example, the model emulates the situation where a patient visits a chest clinic with some symptoms, say the patient is a smoker and has dyspnea as shown by bars with 100% probability. These can be entered as observations and through inference, the probabilities are updated, and it can be inferred that the patient has a high chance of bronchitis as opposed to lung cancer or tuberculosis.

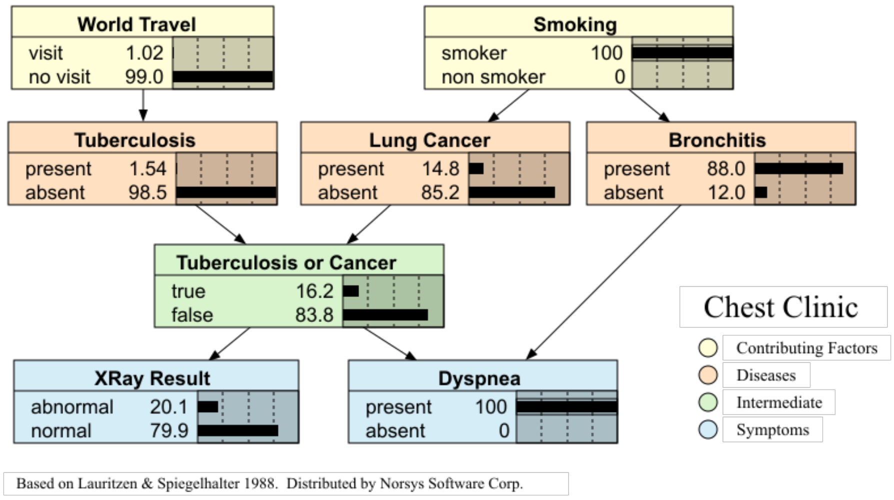


Figure 5.3. Chest clinic example with Bayesian Networks

5.4 Details of the Novel Support Method for Resilience

The main contribution of this work is to develop a quantitative evaluation tool for strategic resilience in engineering infrastructure systems. To this end, the design for flexibility and Bayesian Networks have been identified to be suitable for this analysis. This subsection details this novel support method which is adapted from Cardin's five-phase flexibility cycle (Cardin, 2014). The novel support method framework thus comprises Initial Robust Design, Uncertainty Recognition, Implementation of Flexibility with Bayesian Networks, Design Space Exploration and Resilience Analysis. The relationship between the five steps are shown in Figure 5.4.

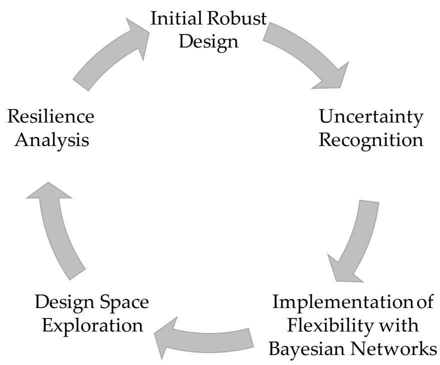


Figure 5.4. Novel support method for resilience

A high-level schema of the computational model is given in Figure 5.5 where some uncertainty model drives the robust and flexible model. In the robust model, there are no technology upgrades over time, while in the flexible model, the Bayesian Network selects an upgrade if appropriate. The Net Present Value (NPV) is then calculated to give a point of comparison between designs.

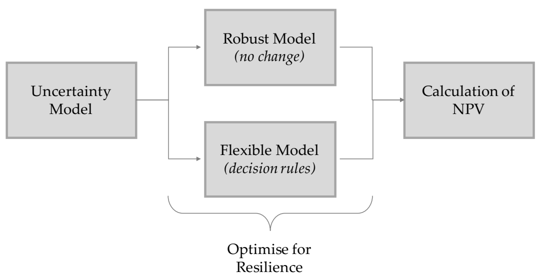


Figure 5.5. Schema of novel support method

5.4.1 Initial Robust Design

This first step assesses the NPV of the system with no flexibility upgrade options to establish a benchmark for comparing to other infrastructure designs generated in latter steps. NPV models are developed under deterministic conditions based on deterministic forecasts for uncertainty factors. The initial robustness of the system can be optimized given these forecasts and there are no flexibility options exercised through the simulation. The NPV, for some time horizon, T, is calculated from:

$$NPV = -C^0 + \sum_{t=1}^{T} \left(\frac{1}{1+\lambda}\right)^t (R^t - C^t) \tag{5.4}$$

where C^0 is the initial setup cost, λ is the discount rate, R^t is the revenue of the system and C^t is the cost function at time step, t. Essentially the NPV calculates the profits or losses in each year and discounts this value over the simulated period accounting for inflation.

5.4.2 Uncertainty Recognition

The system is then modelled subject to uncertainties which may affect future performance. This step identifies these sources of uncertainty through experts' and designers' experience which can be modelled by collecting historic data and statistical analysis. From discussions with stakeholders and following similar previous work in the design of flexibility, the uncertainty of interest will be demand on the system which is typically modelled through geometric Brownian motion. This is modelled as some mean trend with a randomly varying quantity that follows a Brownian motion and formulated in the following equation:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{5.5}$$

where S_t is the demand at time, t, the trend or growth rate is denoted by μ, σ is the volatility and W_t is the Wiener process. The calculation of the Expected Net Present Value (ENPV) then becomes

$$ENPV = \sum_{l}^{L} p_l \left\{ -C^0 + \sum_{t=1}^{T} \left(\frac{1}{1+\lambda}\right)^t (R_l^t - C_l^t) \right\} \tag{5.6}$$

where p_l is the probability associated with scenario l and L is the total number of simulations ran. The other variables are the same as for NPV equation above.

5.4.3 Implementation of Flexibility with Bayesian Networks

The third step of the original flexibility framework was used to identify the components which could be prime targets for change and conceptualise the strategies that could be employed. In this work, it is assumed that the flexible strategies or components for upgrades have been identified and the task is then to choose between the strategies or options. The main contribution of this work thus lies in this step and involves using Bayesian Networks to model the decisions behind system upgrades. In doing so, the trade-off between robustness and flexibility can be analysed for resilience by assessing the thresholds between the strategies.

Case Study 1: A theoretical proof-of-concept

While Bayesian Networks have a strong probabilistic foundation, application for this problem and for resilience has not yet been grounded. To this end, an existing case study investigating flexibility in Waste-to-Energy systems in Singapore (Cardin & Hu, 2015; Hu & Cardin, 2015; Ziqi, 2017) was taken to benchmark this novel Bayesian Network approach and compare results. In the original study, IF statements and thresholds were implemented to model a set of decision rules. This was extended here by using Bayesian Networks as decision rules to determine when to execute the strategy given uncertainties observed on the system. The Bayesian Network used for the study is drawn using Netica, a Bayesian Network modelling software, and shown in Figure 5.6.

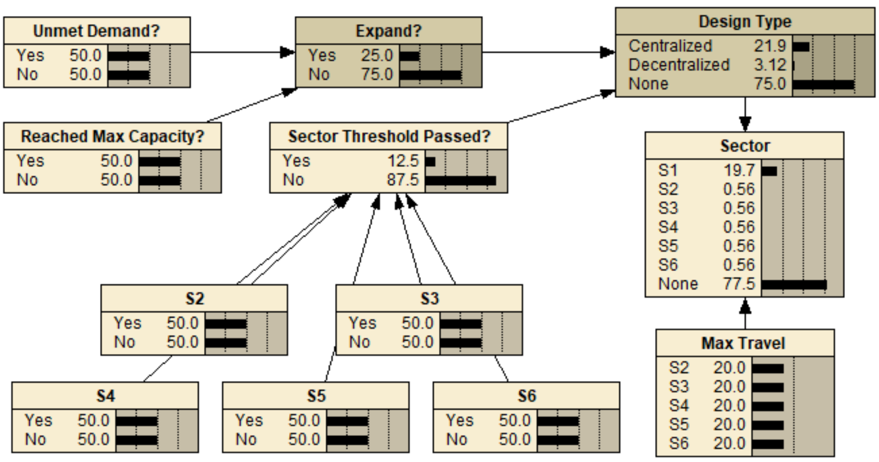


Figure 5.6. Bayesian Network of Waste-to-Energy System

Variables are shown in the boxes with black bars representing the probabilities and arrows representing the dependencies. The binary Yes/No variable states and structure of the network reflect the IF statements used in the original study. The probabilities for the CPTs were thus 100% or 0% given the binary states represented by IF statements. The "Unmet Demand" node represents the uncertainty on the system and S2-S6 are the sectors of the system. These are fed into an options classifier which recommends the "Design Type" and the "Sector" that should be upgraded based on the sector which had the largest travel cost. The network was further coded in MATLAB using the Bayes Net Toolbox developed by Murphy (2002) so that Monte Carlo simulations could be ran and NPV for different scenarios could be computed. The results from Netica, MATLAB and the original study using IF statements were cross-referenced to ensure that the model was implemented correctly.

Although at this stage, using Bayesian Networks may have been over elaborate and it may have been easier to build the model using IF statements, it was necessary to have some validation of this concept for further work. The results obtained using Bayesian Networks, presented in Chapter 6, were shown to be similar to the original study giving confidence for continuation.

Case Study 2: Elaborations with Industry

Having some experience of theoretically implementing Bayesian Networks with the first case study, this approach was then applied with industrial sponsor BT where the task was to understand what and when to change technologies as well as the order of upgrades. The main limitations of Bayesian Networks are that their structure and construction are highly subjective with no standardised framework to guide the process. Thus the challenge of using such models in applied cases pertain to eliciting this information from experts or data. To this end, a series of three workshops were held to elicit the variables, dependencies and assumptions necessary for the model. These were then built in Netica and Python using the *pomegranate* library (Schreiber, 2017) to ensure the model behaved as expected and to interface with further analyses.

The first workshop aimed to give participants a primer on resilience, Bayesian Networks and to validate the objectives for this work. The workshop booklet that was given to participants ahead of time is presented in Appendix A. It should be noted that the definition of resilience based on probabilistic density functions as shown in the booklet has since evolved due to the difficulty in eliciting such functions from experts. There were seven participants from different parts of the research division. Ideally this exercise should be conducted individually such that each expert came up with their own view of the problem and thus structure of the network. However, time constraints meant that this was not feasible and instead conducted as a group exercise. To give some structure to the workshop, Bayesian Networks developed in this work aimed to loosely following the groupings depicted in Figure 5.7.

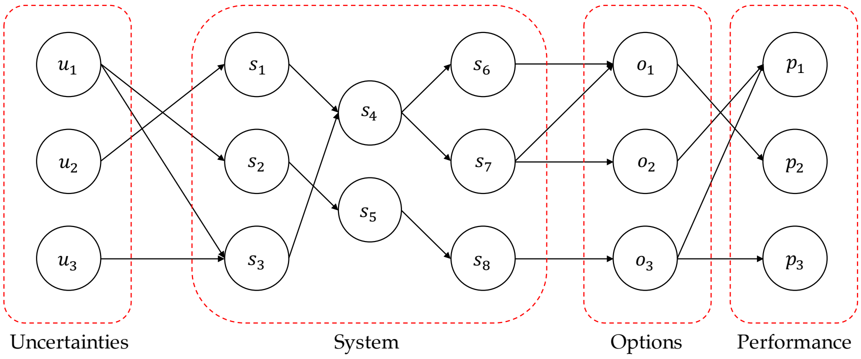


Figure 5.7. Groupings of variables show to participants of workshop to prompt discussion

This structure models uncertainties as an input to some system with outputs to a number of options. The most appropriate option is then classified and the performance of the options are given on the right-hand side. This model is put into this input-process-output form to make it intuitive for users, especially the engineering experts to provide further data. The variable types and descriptions for the model are given in Table 5.1. Furthermore, prompts were given to elicit variables and acted as initial questions to contextualise further discussion with BT experts. Examples are also listed in the table with more details given in the workshop booklet in Appendix A.

Table 5.1. Variable groupings to prompt discussion with workshop participants

Variable Type	**Description**	**Prompt**
Uncertainties	Captures external variables which may affect the system	What are the demands on the NGA network?
System	Models interdependencies in the system	How do the uncertainties impact the network?
Options	Classifies the type of technology per exchange	How does the system affect the choice of technology?
Performance	Gives the performance of the chosen technology	What performance metrics are important for NGA 2.0?

The group suggested 25 variables of interest in the first workshop but time constraints meant that the dependencies and probabilities were not fully captured. After the first workshop the variables were grouped similarly to the layout above with dummy dependencies based on the author's assumptions to test the model and in particular, the "system" was further split into physical characteristics, such as distance from exchange to cabinet, and business considerations, which included whether the service level agreement was met. This leveraged upon the ability for the Bayesian Network to capture a wider range of considerations, both qualitative and quantitative. Figure 5.8 shows these groupings on the network, reorganised by the author, after Workshop 1.

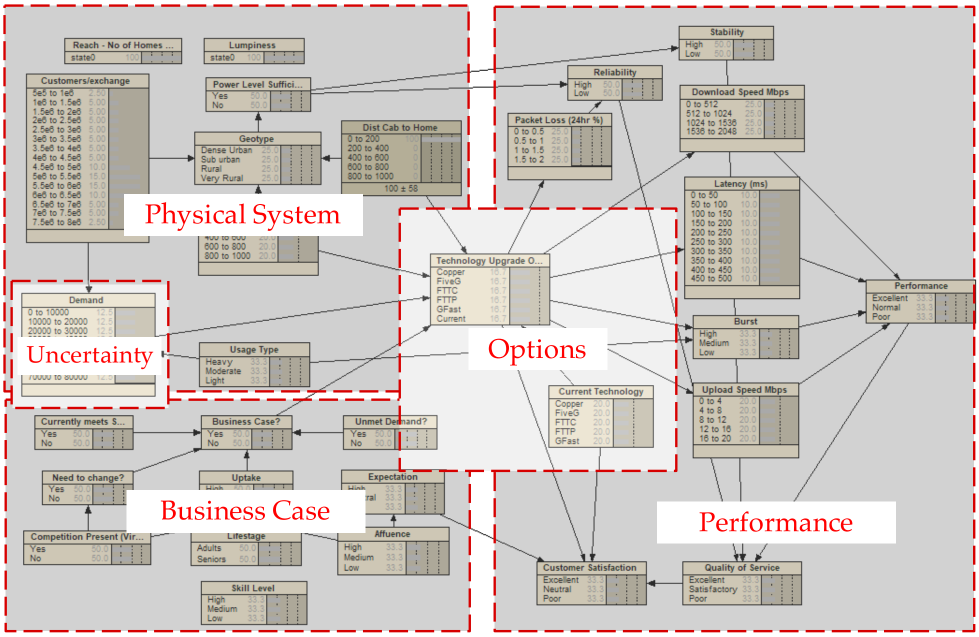


Figure 5.8. Bayesian Network groupings after Workshop 1

These discussions and layout of the network also allowed for the decision rules to be established as shown in Figure 5.9. At the top of the figure, business considerations are aggregated to decide whether there is a business case and if there is, whether the upgrade should be an increase in throttle or a switch in technology. This is determined by the physical characteristics of the system.

A second workshop was organised and a workshop debrief of the first workshop outlined further work. This included refining the discretisations of the variables and some clarification of the variable definitions. With three participants from the network design group, the model was refined, growing to 30 variables. The dependencies were filled in through a Design Structure Matrix (DSM), also known as an adjacency matrix in graph theory. An example DSM given to participants

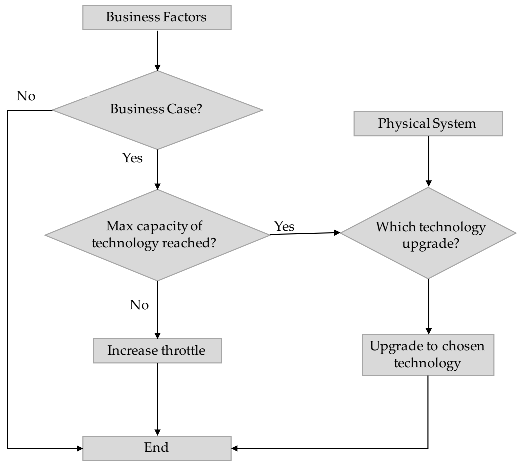


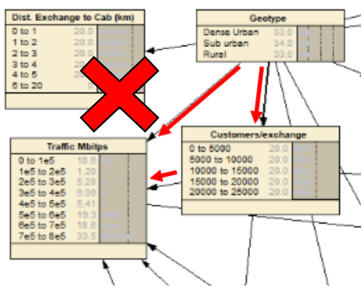
Figure 5.9. Decision rules for BT case study

for reference in Workshop 2 is shown in Figure 5.10. Reading along the rows and down the columns, the variable's outputs and inputs can be recorded respectively. For example, the "Business Case" node has inputs from "Unmet Demand", "SLA level", "Skill level" and "Uptake". The node then outputs to "Technology Option" to determine whether to upgrade or not. The filled in DSM resulted in 127 connections between 30 nodes. However, this became difficult to implement due to the large conditional probability tables (CPTs) as well as long computation times for inference and had to be simplified.

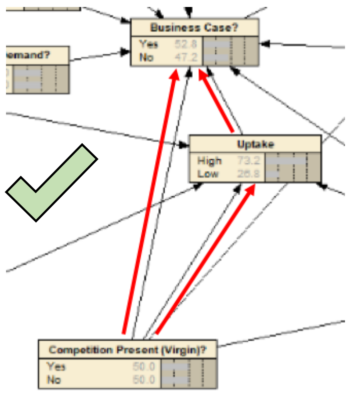
	Customer/Exch	Geotype	Dist Exch to Cab	Dist Cab to Home	Traffic	Usage Type	Power Level	Lumpiness	Reach	Business Case	Unmet Demand	SLA level	Skill Level	Uptake	Expectation	Competition Present	Lifestage	Affluence	Technology Option	Current Technology	Customer Satisfaction	Quality of Service	Upload Speed	Download Speed	Burst	Latency	Stability	Reliability	Performance	Packet Loss
Customer/Exch																														
Geotype	x		x	x																										
Dist Exch to Cab																														
Dist Cab to Home																														
Traffic	x					x																								
Usage Type																														
Power Level		x																												
Lumpiness																														
Reach																														
Business Case											x	x	x	x																
Unmet Demand																														
SLA level																														
Skill Level																														
Uptake																x	x	x												
Expectation																x	x	x												
Competition Present																														
Lifestage																														
Affluence																														
Technology Option			x	x	x					x										x										
Current Technology																														
Customer Satisfaction															x				x	x		x								
Quality of Service																											x	x	x	
Upload Speed																			x											
Download Speed																			x											
Burst					x														x											
Latency																			x											
Stability							x																							
Reliability							x																							x
Performance																							x	x	x	x				
Packet Loss																			x											

Figure 5.10. Example DSM given to participants for reference

Since Bayesian Networks represent acyclic graphs, cyclical dependencies were first removed. In doing so, it was useful to think of the flow of the graph from input uncertainties to output technological performance. The cycles mainly arose from the performance metrics of the network then driving the system again. For example, having a good performance, such as high download bandwidth would then attract more customers and in turn a high demand input. These cycles were removed to make the performance nodes the end "leaf" nodes in the network. The matrix was further reorganised into upper triangular form to check for cycles. Some nodes, such as whether there was unmet demand, also had many inputs making the CPTs hard to generate since the conditional probabilities are exponential with the number of parent nodes. Further dependencies were thus removed if there was a similar indirect path between the nodes through some intermediary node and the influence of the parent nodes were similar. For example in Figure 5.11.a, it can be assumed that having a certain geotype will influence the number of customers in the exchange and in turn the amount of traffic. While the direct link from geotype and traffic is also logical, it is assumed that this information can also be inferred from the customers per exchange such that this extra link provides no new information. In Figure 5.11.b, however, the direct dependency from competition to business case is kept because the uptake and whether there is the presence of competition can affect whether there is a business case differently.



(a) Example where extra dependency (Geotype to Traffic) was removed



(b) Example where dependency was kept

Figure 5.11. Examples of simplification of the network

The "divorcing nodes" technique was also used and is where intermediate nodes are introduced to aggregate dependencies in order to reduce the number of inputs to any one node (Nielsen & Jensen, 2009). For example, the "business case" node was introduced to account for all variables pertaining to organisational considerations and acts as an aggregate node before connecting to the "Technology Options". An illustration of this technique is given in Figure 5.12. Considering the diagram where each node can have i states and k parent nodes with n number of states. This would give $i \cdot n^k$ probability values for the CPT. As an example, if X_c in Figure 5.12.a has four states ($i = 4$) and three parents, X_{p1}, X_{p2}, X_{p3}, ($k = 3$) with four states each ($n = 4$), there would be 256 resulting values needed for the CPT. If an intermediate node is introduced, as in Figure 5.12.b, both X_c and X_m would need 64 values, giving a total of 128 values.

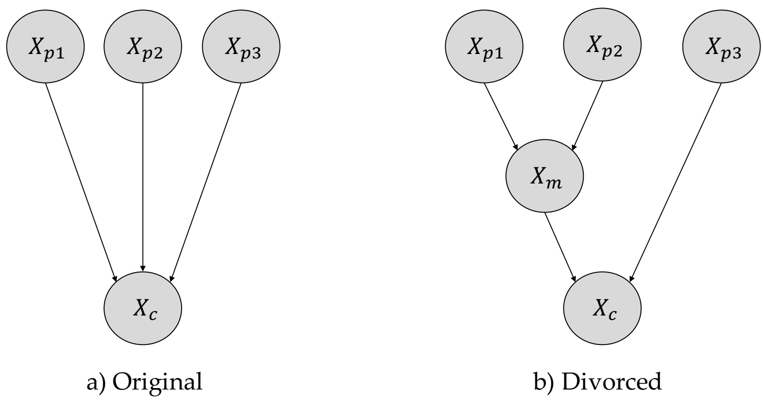


Figure 5.12. Illustration of divorcing technique to reduce the number of inputs

Another pertinent challenge with the Bayesian Network approach was the discretisation of continuous variables. This obviously is not an issue for discrete nodes such as whether there is a business case, but for nodes such as the distances from exchange to cabinet or amount of traffic, the size or number of discretisations became a problem: having too large an interval meant information was lost, but on the other hand, if the intervals were too small, the CPTs grew exponentially. To this end, minimum and maximum values were computed or assumed and ranges are calculated to give 5 discretisations to balance computational time and granularity. The traffic node, however, was split into 8 intervals due to its importance in driving the system. Further study should be taken to assess for sensitivity and the distribution of real data for the nodes should also be investigated. That said, since the majority data for this model is assumed for now, this was to be explored in future work.

Further refinement involved removing variables and dependencies which were not crucial upon discussions from the third workshop and resulted in a final network with 28 nodes and 51 connections. The final DSM showing the dependencies are presented in Figure 5.13 while the evolution of the Bayesian Network through the workshops are shown in Figure 5.14 and a description of all the nodes are given in Table 5.2.

	Geotype	Customers/Exchange	Dist Exch to Cab	Dist Cab to Home	Lifestage	Affluence	Usage Type	Traffic	Reach	Lumpiness	Throttle	Current Technology	Unmet Demand	SLA level	Skill Level	Expectation	Competition Present	Uptake	Business Case	Technology Option	Power Level	Upload Speed	Download Speed	Burst	Latency	Reliability	Quality of Service	Customer Satisfaction
Geotype		x	x	x	x	x			x	x																		
Customers/Exchange								x					x								x							
Dist Exch to Cab																												
Dist Cab to Home																				x		x	x	x		x		
Lifestage							x											x										
Affluence							x											x										
Usage Type								x																				
Traffic													x	x						x								
Reach																			x									
Lumpiness																												
Throttle													x							x								
Current Technology													x							x								x
Unmet Demand																			x									
SLA level																			x									
Skill Level																			x									
Expectation																		x	x									x
Competition Present																		x	x	x								x
Uptake																			x									
Business Case																				x								
Technology Option																					x	x	x	x	x	x		x
Power Level																												
Upload Speed																												
Download Speed																												
Burst																											x	
Latency																												
Reliability																											x	
Quality of Service																												x
Customer Satisfaction																												

Figure 5.13. Final DSM in upper triangular form to check for cycles

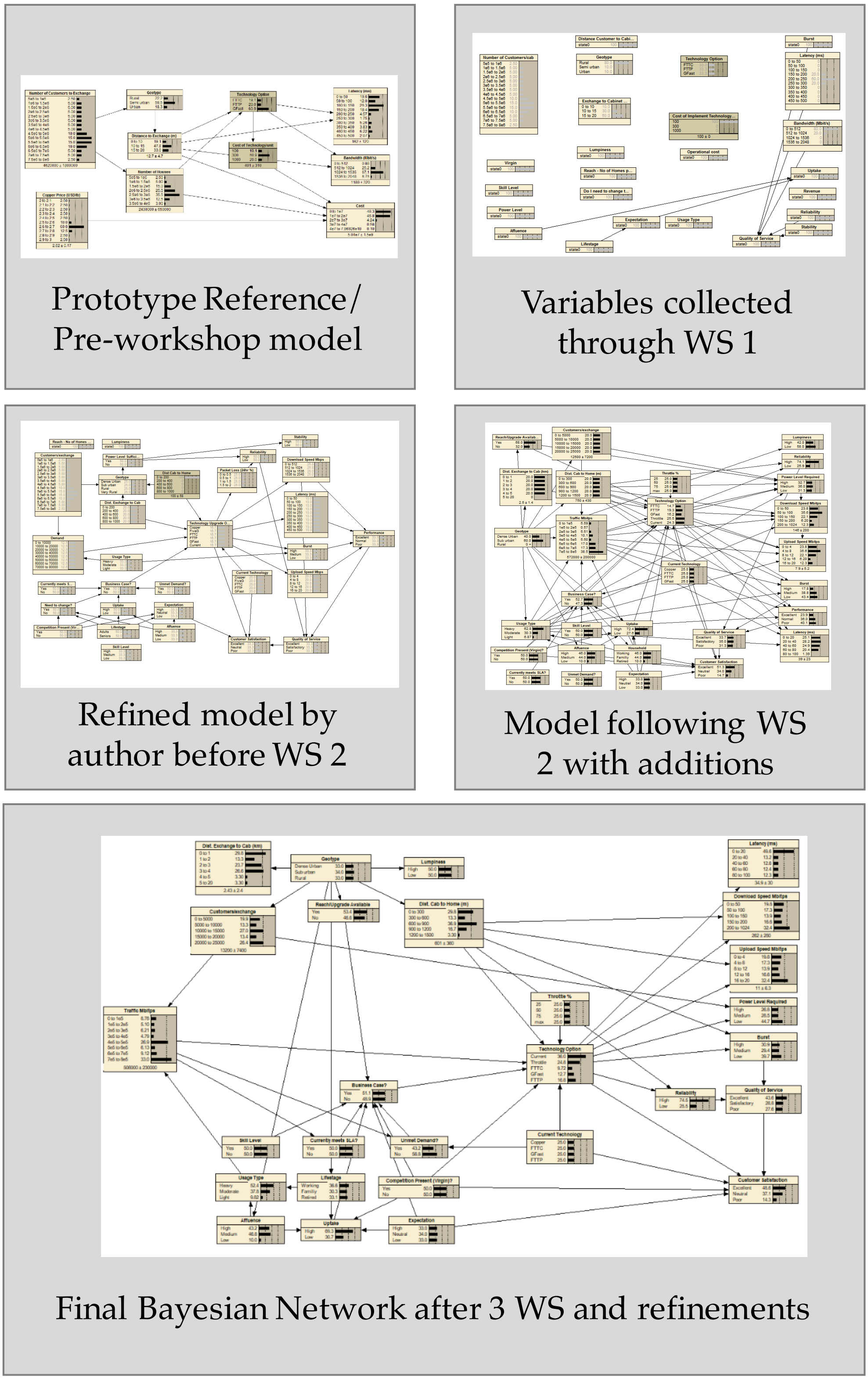


Figure 5.14. Evolution of the Bayesian Network model through the workshops (WS)

Table 5.2. Node descriptions for final network

Node Name	Description
Traffic	Amount of data going through exchange. Demand from geometric Brownian motion simulations.
Dist. Exchange to Cab (km)	Distance from the exchange to cabinet.
Customers/Exchange	Number of customers per exchange.
Geotype	The type of area characterisation.
Availability	Whether the technology upgrades are available in the area.
Spread	Whether the spread of houses in the area is uniform or clustered.
Dist. Cab to Home (m)	Distance from cabinet to home.
Business Case?	Whether there is a business case.
Skill Level	Whether engineers in the area have sufficient skills to install new technology.
Currently meets SLA?	Whether the area is currently meeting Service Level Agreements.
Unmet Demand?	Whether the demand/traffic is great than that installed.
Usage Type	Whether the customers use data heavily (i.e streaming TV).
Lifestage	The type of residents in the premise.
Competition Present (Virgin)?	Whether there is competing companies in the area.
Affluence	The wealth of the area.
Uptake	Whether customers may opt for the technology once installed.
Expectation	The customers' belief in the technology.
Throttle %	The amount of throttle applied.
Technology Option	The technology to be installed in that year, if any.
Current Technology	The technology that is currently installed that year.
Latency (ms)	The delay of data transfer.
Download Speeds (Mbit/s)	The speed at which data can be transferred from internet to computer.
Upload Speed (Mbit/s)	The speed at which data can be transferred from computer to internet.
Power Level Required	How much electricity is required.
Burst	Whether there are spikes in demand.
Quality of Service	Performance measure of the network.
Reliability	Whether the data is transferred successfully.
Customer Satisfaction	Whether the customers are satisfied with the service.

To finish building the Bayesian Network, the CPTs underlying each node had to be elicited from experts. For simple cases with small CPTS, these could be input directly by asking experts to make some judgement of the probability. The Bayesian Network was built in Netica (Norsys Software Corp, 2018) to visualise and verify the model's behaviour. Netica was useful in providing a drag and drop interface to construct Bayesian Networks as well as input CPTs allowing for quick modifications and iterations with experts. An example of the CPT for the number of customers per exchange node is given in Figure 5.15. For this CPT, it is estimated that for dense urban areas, there is a 20% and 80% probability of having 15,000 to 20,000 and 20,000 to 25,000 customers respectively. For rural areas, it is estimated at there is a 50% chance of having 0 to 5,000 customers, 30% of 5,000 to 10,000 and 20% of having 10,000 to 15,000 customers. This is input similarly for all the other nodes with small CPTs.

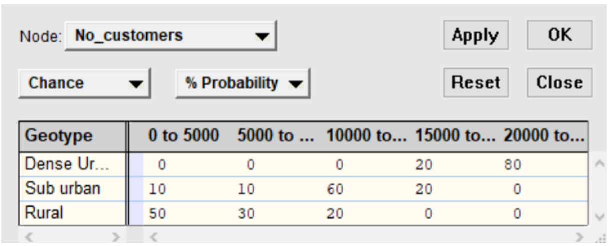


Figure 5.15. Conditional Probability Table for number of customers

As highlighted before, the number of entries in the CPT grows exponentially with the number of dependencies and it was not practical to ask industry experts to fill in all the tables. Indeed, the final "Technology Node" resulted in the need for 12,800 entries since it has 5 states and 6 inputs with 4, 5, 8, 2, 2, 4 states respectively. While the CPT and also the structure of the network may be learned from data, there has been difficulty in sourcing such a dataset, especially across domains of BT. Instead, an algorithmic approach was taken to generate full CPTs from expert insight and functions were coded in MATLAB to output the CPTs. The approach taken here is shown by example below. Consider filling in the "Quality of Service" CPT, as shown in Figure 5.16. The node has 3 states and 2 inputs, reliability and burst, with 2 and 3 states respectively. The CPT is generated by eliciting a key with the expert which maps from the states in the input node to the "Quality of Service" node as shown in Table 5.3 and Table 5.4.

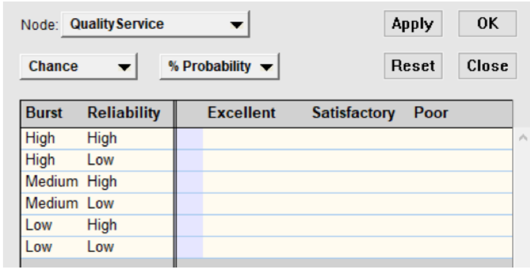


Figure 5.16. Conditional Probability Table for quality of service

Table 5.3. CPT mappings for Quality of Service node

Burst	**Quality of Service**		
	Excellent	Satisfactory	Poor
High	80	20	0
Medium	10	80	10
Low	0	20	80

Table 5.4. CPT mappings for Reliability node

Reliability	**Quality of Service**		
	Excellent	Satisfactory	Poor
High	80	20	0
Low	0	20	80

The CPT is obtained by summing according to the keys, then normalised so that each row sums to 100%. This approach was presented in the second workshop for nodes which involved many variables and the keys were iterated by the participants. The model and probabilities were iterated by the author after the workshop to make the Bayesian Network give expected behaviour. For example, if there is high traffic, the highest capacity technology, FTTP, should be recommended. This was presented again to experts in the third workshop for further refinements. This was then coded into Python, using the *pomegranate* library (Schreiber, 2017) to build the Bayesian Network and further interface with code to calculate the NPV for each exchange as well as post-processing. The Bayesian Network implementation in Python was similar in that it required the specification of nodes, edges and CPTs. Netica was also cross-referenced to the Python code to check the Bayesian Network was behaving as intended. A significant problem of this was the computational time to input observations, do inference between variables and get results for every time step in the Monte Carlo simulation. To this end, a lookup table was made so that the value could be taken directly, leading to an 80% reduction in computational time.

5.4.4 Design Space Exploration

With the Bayesian Networks developed, the fourth step involves evaluating the ENPV of the system with the embedded flexibility. The Monte Carlo method generates a range of simulations and the Bayesian Network recommends upgrades, if any, depending on uncertainties observed at that current time step. This Bayesian Network recommendation can be visualised in Netica, shown for the BT case study in Figure 5.17, where the grey boxes represent an observation in the node. In this case, observations are input into the nodes "Traffic", "Distance Cabinet to Home", "Throttle" and "Current Technology".

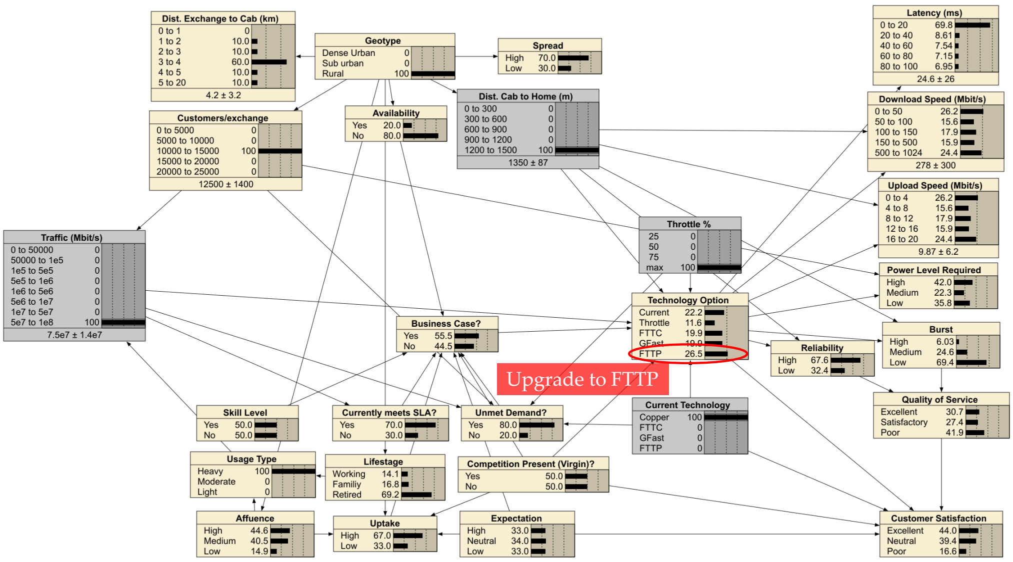


Figure 5.17. Visualisation of observations on the system and recommendation from Bayesian Network

The state with maximum probability in "Technology Option" node is taken to be the recommendation of the technology for the next time step and in this case, the Bayesian Network recommends to upgrade to FTTP. The business requirements of what, when and order of technology upgrades can therefore be found using the Bayesian Network. The different design options, such as increasing initial capacity or Bayesian Network characteristics through the CPT, can then be compared with the Initial Robust Design in Step 1 where there is no flexibility. This allows the designers to discern whether the flexible strategy is worth the additional investment cost by calculating the difference between the ENPV of the flexible design and the NPV of the fixed design in Step 1. The ENPV can therefore be optimised through different configurations of design strategies.

5.4.5 Resilience Analysis

The business and technical requirements for this work have been met through the implementation of the Bayesian Network in the previous steps. This step looks at how these decisions are affected under varying volatility and drift to understand how the upgrades through time are affected. The conceptual requirements for resilience further seek to understand the trade-off between robustness and flexibility and the results produce a trade-off surface for analysis. Here, the robustness can be examined by looking at the initial capacity of the system and flexibility accounted for through the maximum number of upgrades. Furthermore, the model is then extended by varying the volatility and drift of the demand to explore the effect of different uncertainty predictions which underpin resilience. As such, the resilient designs are those which maximise ENPV for some given demand prediction.

5.5 Summary

This chapter brought together the business, conceptual and technical requirements to synthesise the novel support method for this work. While the Least Squares Monte Carlo method used in Chapter 4 satisfied the business requirement of understanding what to invest in, it was limited in the types of uncertainties it could capture and relied heavily on a financial approach. To this end, Bayesian Networks were presented here to address these shortcomings and was incorporated into the five-phase flexibility framework discussed in Chapter 4. The five-phase process for this work is therefore: Initial Robust Design, Uncertainty Recognition, Implementation of Flexibility with Bayesian Networks and Resilience Analysis. Further particulars of each step in the framework was outlined so that it could be applied for the case studies in Chapter 6 and assess for resilience.

Extra elaboration on the third step of the process, which presents this work's main contribution, is given and describes the elicitation process of the Bayesian Network from industry experts through a series of three workshops. This is particularly important to record due to the subjective nature of building Bayesian Network models. The workshops involved familiarising participants with resilience and Bayesian Network concepts, validating the requirements of the model, determining the nodes and dependencies of the network, dicretisation of the variables and computing the conditional probability tables for the Bayesian Network. This was then coded in Python so that the ENPV could be calculated with the stochastic demand and further analysis be performed.

Chapter 6

Application of Support Method

The proposed support framework from Chapter 5 is applied to two case studies in this chapter. The first is an application to the development of Waste-to-Energy Systems in Singapore and is used as a proof-of-concept by benchmarking the support method against existing models developed by Hu & Cardin (2015) and Ziqi (2017). The second case study models telecommunications investments in Cambridgeshire for BT to understand the use of this framework in practice. This involved a series of three workshops at BT to elicit the structure of the Bayesian Network, obtain probabilistic data and to iterate through improvements to the model as described in Chapter 5. Both cases examine how robust to initially make the system and the flexible upgrades that should be delivered to respond to appropriately to demand uncertainty. In doing so, different design strategies for these engineering infrastructure systems are investigated and therefore the resilient designs are those combinations which maximise the ENPV under various demand assumptions.

6.1 Case Study on Capacity Expansion in Waste-to-Energy Systems

The resilience framework is first applied to Waste-to-Energy (WTE) systems based in Singapore and the impact of combining robust and flexible design strategies to improve resilience are explored. This builds on work by Hu & Cardin (2015) and Ziqi (2017) where a NPV model has been built to assess the merits of flexible expansion and also based on the real options paradigm. Here, Bayesian Networks are further implemented to simulate similar decision rules as in their work to demonstrate a theoretical benchmark for this framework. The Bayesian Network chooses the flexible expansion strategy that should be deployed given the current observations of demand uncertainties. Robust strategies involve optimizing for the initial maximum capacity of the system while flexibility allows for future upgrades in the system. Resilience is then further evaluated by varying the drift and volatility of the stochastic demand in the simulation to assess the impact on the ENPV and to understand the merits of different infrastructure designs.

6.1.1 Background of Case Study

Singapore is divided into six sectors by public waste collector contractors which collect waste within each sector before transporting to a centralised processing plant, shown as Sector 1 in Figure 6.1. An alternative option exists for five smaller processing plants to be added in a decentralised manner, labelled as Sectors 2-6, and in such a case, instead of transporting the waste to a main site, the waste can be also be processed in each of the five non-main sectors. This decentralised system could be a potential solution to combat increasing waste generation and providing a more economic waste processing method. Furthermore, this case models waste processing through Mechanical Biological Treatment Technology with anaerobic degradation which utilises mechanical and biological processes to handle unsorted solid and residue waste before landfilling.

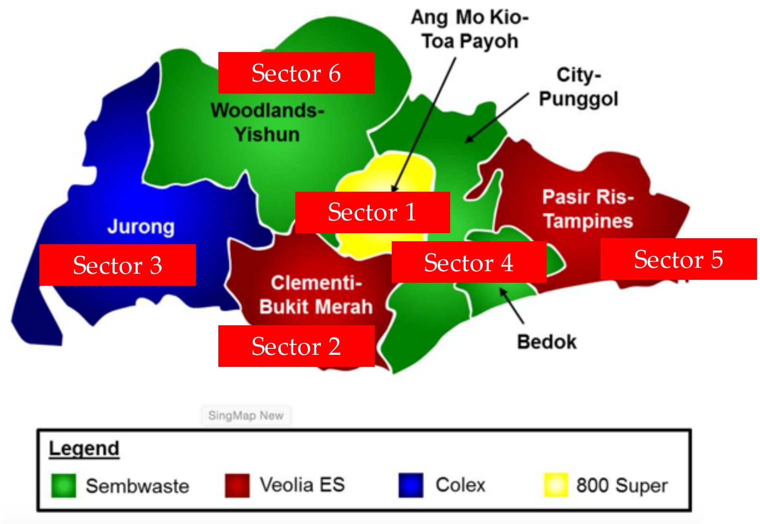


Figure 6.1. Sectors for Singapore waste disposal, adapted from Ziqi (2017)

The objective of this case study is therefore to assess the merits of moving to a decentralised system, which site to expand in and evaluate how to design the system so that it is resilient to short term and long term fluctuations in demand. Following the framework outlined in Chapter 5, the first step separately models and compares the centralised and decentralised system with no increases in capacity, forming the robust model. In the uncertainty recognition step, the demand on the system is simulated for each sector for 15-year time periods. For the decentralised case, the sectors for capacity expansion, whether in the main site or non-main sectors, are selected through the Bayesian Network representation of the decision rules, while in the centralised system, only the main site is considered for expansion. The ENPV is then calculated and the volatility is varied to understand the impact of different design choices on the initial capacity and number of upgrades. This case study therefore illustrates how the support method can be used to choose between the technology options to be deployed, when to implement change and how the design strategies affect resilience and NPV value. The design considerations are summarised in Table 6.1.

Table 6.1. Design considerations for Waste-to-Energy case study

Design Choice	**Available Options**
Site Locations	Main/Non-Main sectors
Design Strategy	Robust/Flexible

6.1.2 Initial Robust Design

There are two main design concepts for the WTE system: the original centralised system and decentralised development. Both of these are simulated with deterministic demands for each technology option with fixed capacity in the first instance to give a benchmark NPV for comparison in later stages.

Model Development of Centralised Design

To calculate the NPV of the centralised WTE system, the model is constructed by considering a planning horizon of $T = 15$ time periods where demand is assumed to be known. The total capacity installed is denoted by x, and d^t is the total capacity demand at time, t. The NPV may therefore be maximized over the planning horizon by finding the capacity x, which fulfils demand, d as follows

$$\begin{aligned} \max \quad \text{NPV} = -C^0(x) + \sum_{t=1}^{T} \left(\frac{1}{1+\lambda}\right)^t \left[R^t(x, d^t) - C^t(x, d^t)\right] \\ s.t \quad 0 \leq x \leq x_{\max}, \quad d^t \geq 0, \forall t \end{aligned} \tag{6.1}$$

$C^0(x)$is the initial cost of investing into the plant, λ is the discount rate, $R^t(x, d^t)$ is the revenue of the system and $C^t(x, d^t)$ is the cost function in time. The revenue of the WTE systems at year t consists of the selling revenue from refuse derived fuel (R^t_{RDF}), metal (R^t_M), biogas (R^t_B), and water (R^t_W) as well as a tipping fee for collecting solid waste (R^t_{Tip}). This is given by the equation:

$$R^t = R^t_{RDF} + R^t_M + R^t_B + R^t_W + R^t_{Tip} \tag{6.2}$$

These are assumed to be proportional to the amount of waste treated in the plant. The costs involved with the centralised design include: transportation cost (C^t_{TS}), disposal cost (C^t_D), land rental cost (C^t_{LD}), operation and maintenance cost (C^t_{OM}), resource consumption cost (C^t_{RC}) and pollution cost (C^t_{PL}). This is summarized in the equation below:

$$C^t = C^t_{TS} + C^t_D + C^t_{LD} + C^t_{OM} + C^t_{RC} + C^t_{PL}. \tag{6.3}$$

The transportation cost results from the fuel consumption for collecting the waste in each sector and transporting it to the central facility. There is a cost of disposal incurred when there is unmet demand in the WTE plant and the untreated waste needs to be disposed at incineration plants or landfills. The land rental cost is proportional to the land needed for installed capacity, while the operational and maintenance cost is assumed to be proportional by some coefficient, π to the initial cost. The WTE system consumes energy including electricity and natural gas and is assumed to be proportional to the amount of solid waste treated. The cost of pollution results from the cost of treating the CO_2 emissions from the WTE system.

Model Development of Decentralised Design

The calculations for the decentralised design are similar to those for the centralised design, but instead of having all the waste transported to one central site, the waste can be transported to the main site or one of the five decentralised plants in the different sectors. The total demand, d^t, is assumed to be distributed among the six sectors according to population density of the sector. The total capacity, x, is therefore the sum of the capacity in each sector. The total revenue is calculated accordingly by summing over the six sectors. The NPV model for the decentralised design is therefore

$$\max \quad \text{NPV} = -\sum_{i=1}^{6} C^0(x_i) + \sum_{t=1}^{T}\sum_{i=1}^{6}\left(\frac{1}{1+\lambda}\right)^t \left(R^t - C^t\right) \tag{6.4}$$

With the models for the centralised and decentralised models defined, the NPVs for both designs are calculated for a 15-year horizon with the demand deterministically projected based historical data from the National Environmental Agency (NEA) annual report (National Environment Agency Singapore, 2017). For the centralised model, given growth rate μ, the waste is given by the equation

$$S^t = S^{t-1}(1+\mu) \tag{6.5}$$

where S^t is the waste generated at year t. For the decentralised case, the amount of waste in each sector is estimated from the population density, p_d, in each sector, i, from

$$S_i^t = p_d S^t \tag{6.6}$$

To make the modelling of the design capacity more practical, the capacity is assumed to be in multiples of 50 tonnes per day (tpd). A simulated annealing optimization was conducted to find the optimal configuration of initial capacity in each sectors to maximize the NPV. For the centralised design, an optimal initial capacity of 5200 tpd gave a NPV of S$243 million. The initial capacities for each sector and NPV for the decentralised design is summarized in Table 6.2. For these results, the optimal decentralised design is shown to surpass the centralised design with a NPV of S$251 million. This is due to the savings in the transportation cost in the decentralised design.

Table 6.2. NPV of fixed decentralised design analysis

NPV (S$ Million)	**Initial Capacity**						**Total Capacity (tpd)**
	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	
251	1450	900	850	800	550	500	5050

6.1.3 Uncertainty Recognition

The previous step used a projection for demand on the system based on a fixed growth rate. In reality, this is seldom the case and uncertainty is now introduced into the model in this step by modelling waste generation in each site with geometric Brownian motion. This is formulated in the following equation

$$dS_i^t = \mu S_i^t dt + \sigma S_i^t dW_t \tag{6.7}$$

where S_i^t is the waste collected in sector i, μ denotes the trend or growth rate, σ is the volatility and W_t is the Wiener process. The growth rate and volatility are estimated to be 0.0171 and 0.0203 respectively by fitting a normal distribution to historical data (Ziqi, 2017). A Monte Carlo Simulation is run 2000 times and the ENPV for the centralised model can be obtained from

$$\text{ENPV} = \sum_{l}^{L} p_l \left\{ -C^0(x) + \sum_{t=1}^{T} \left(\frac{1}{1+\lambda} \right)^t (R_l^t - C_l^t) \right\} \tag{6.8}$$

where p_l is the probability associated with scenario l and $L$is the total number of simulations ran. The decentralised model is similarly

$$\text{ENPV} = \sum_{l}^{L} p_l \left\{ -\sum_{i=1}^{6} C^0(x_i) + \sum_{t=1}^{T} \sum_{i=1}^{6} \left(\frac{1}{1+\lambda} \right)^t (R_l^t - C_l^t) \right\} \tag{6.9}$$

Running the simulations with uncertain waste generation, the optimal initial capacity for the centralised design is 5200 tpd giving an ENPV of S$242 million. The decentralised case is summarized in Table 6.3. The ENPV for both cases are, as expected, less than the NPV as calculated in the previous step due to the uncertainty added into the system. Again, the decentralised case performs better than the centralised case.

Table 6.3. ENPV of fixed decentralised design under uncertainty

NPV (S$ Million)	**Initial Capacity**						**Total Capacity (tpd)**
	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	
250	1600	900	850	800	550	500	5200

6.1.4 Implementation of Flexibility with Bayesian Networks

The previous two steps incorporated an optimization to find the initial robust margins for initial capacity. This step now incorporates flexibility into the analysis in order to understand how the system can change for future needs. The flexible strategy to expand the capacity of the WTE plants after installation is simulated with the demand fluctuation being the major uncertainty. This allows for the WTE plant to expand modularly given an increase in demand, but also mitigates risk of having too large a site if the forecast demand is not met. Decision rules are established to determine when to enable the flexible strategies. The decision rules for expanding capacity in the centralised case are simply to check whether there is unmet demand and if there is, the system upgrades capacity subject to being within the maximum capacity of the system. The decentralised case is similar: (1) Determine if there is unmet capacity and whether the total capacity is less than the maximum capacity after expansion. (2) Determine whether the main site or non-main sites should be expanded. (3) Select one of the five non-main sectors for expansion if the main site is not to be expanded. This is summarized in Figure 6.2.

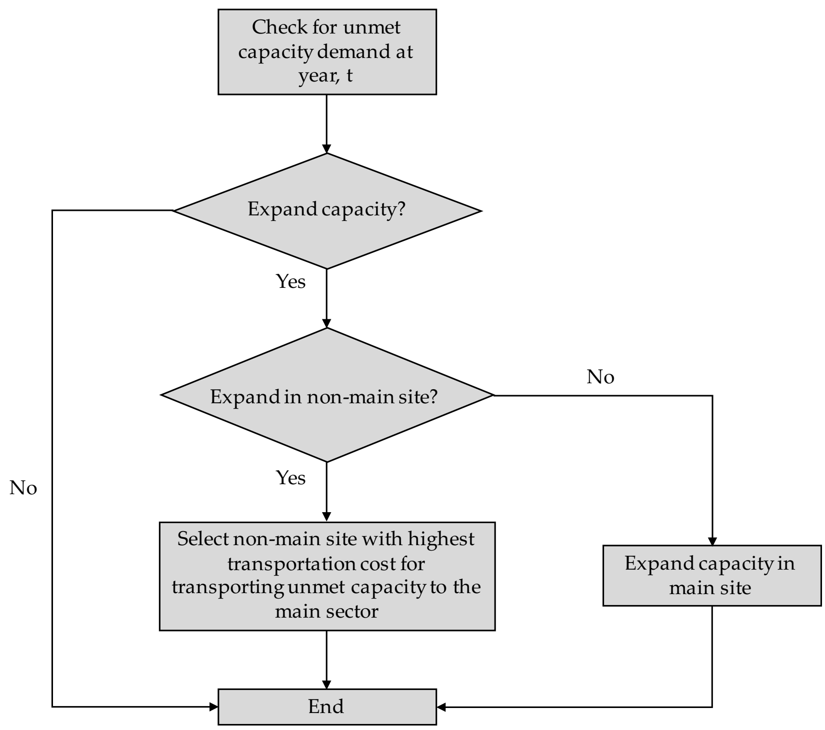


Figure 6.2. Decision Rules for decentralised Waste-to-Energy System

Here, Bayesian Networks are presented to capture these decision rules. Bayesian Networks are chosen in particular for the ability to capture a range of uncertainties, both qualitative and quantitative, the power of using inference for causal reasoning as well as providing an intuitive interface for the decision maker to visualize interdependencies. Bayesian Networks are directed acyclic graphical models which are used to represent a set of variables and their interdependencies. The variables are shown as nodes and the interdependencies, input via conditional probability tables, are represented as edges in the graph. Observed variables, say whether there is unmet demand in year t, can be input into the network and the probabilities of the other variables can be updated through inference in the network. The Bayesian Network in this study is setup to assess whether the decentralised design needs to be upgraded and, in the case that an expansion is necessary, the sector that should be upgraded is indicated. Figure 6.3 shows a screenshot from Bayesian Network software, Netica, for illustration of the Bayesian Network.

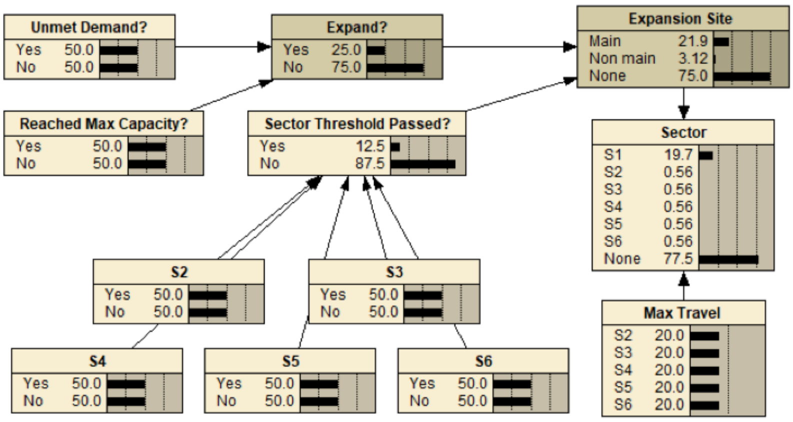


Figure 6.3. Bayesian Network for Waste-to-Energy System

Each box, or node represents a variable and the black bars show the prior and posterior probabilities of the states. The Boolean decisions, for example, whether to expand or not, are represented as yes or no states in the nodes. The nodes S2–S6 hold information on whether the non-main sector capacity thresholds have been breached. If all the sector thresholds are exceeded, the "Sector Threshold Passed?" node updates to yes. The "Expansion Site" node indicates whether the expansion should be in the main site or non-main sites, if any, and depends on observations given in the nodes "Expand?" and "Sector Threshold Passed?". The "Sector" node then classifies which sector should be expanded, if any, given observations from the "Max Travel" node. The "Max Travel" node indicates the sector which incurs the maximum travel cost.

One major advantage of network inference from an uncertainty point of view, is that not all variables have to be observed for the probabilities to be updated. This allows a decision maker to understand the impact of what-if scenarios on the system with limited information and decide whether the system should be changed or in this case, expanded. For example, the following figure shows the Bayesian Network with observations in the greyed-out nodes: “Expand?” = yes, “Sector Threshold Passed?” = yes and “Max Travel” = S5. The rest of the network updates through inference and indicates that the expansion should be in a non-main site as shown in Figure 6.4. This is due to the observation that the sector capacity thresholds have been passed. Had the thresholds not have been exceeded, expansion in the main site would have been recommended. The sector to be expanded, as shown in the “Sector” node is S5, which follows from the “Max Travel” observation and indicates the sector with the highest travel cost to offset unmet demand. The network also indicates that all sectors, nodes S2-S6 are likely to have exceeded the threshold.

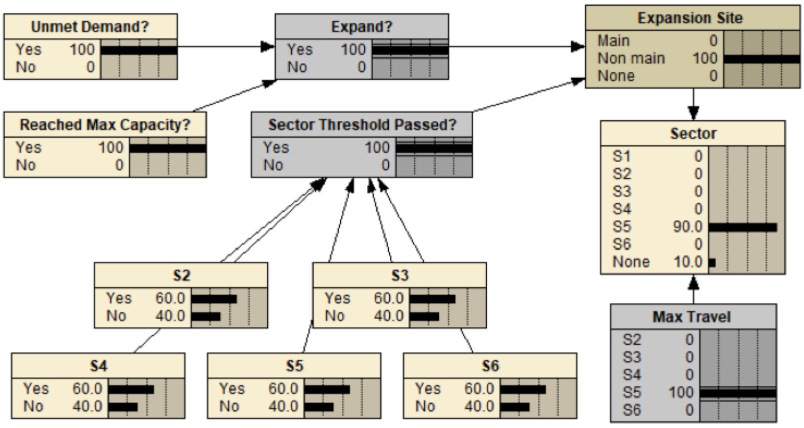


Figure 6.4. Bayesian Network for Waste-to-Energy System with observations

A powerful property of the Bayesian Network is that inference can be used to understand both cause-to-effect, as above, as well as be used to investigate effect-to-cause. That is, in the above example, observations were entered to understand in which sector to expand. Going the other way, the decision maker may want to investigate what conditions are necessary for a main site expansion. This is illustrated in Figure 6.5 where main in the “Expansion Site” node has been observed. The necessary conditions for expansion in the main site are therefore: the system has to have unmet demand, maximum capacity has to have been reached and the decentralised sectors have not passed the capacity thresholds. Furthermore, the sector recommended for expansion is S1 which represents the main site. The Bayesian Network was tested against previous work (Hu & Cardin, 2015; Ziqi, 2017) to ensure similar results and functioning. The simulation can now be ran similarly to Step 1 and Step 2 but with the revenues and costs reflecting whether the sectors have been upgraded as decided by the Bayesian Network.

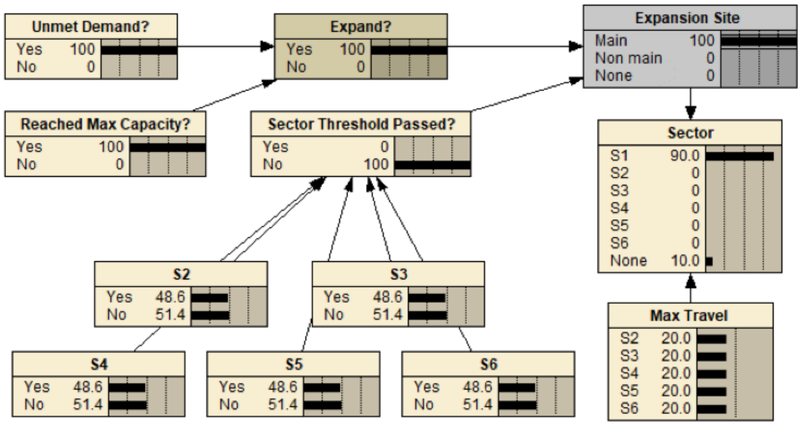


Figure 6.5. Bayesian Network for Waste-to-Energy System with backwards inference

6.1.5 Design Space Exploration

With the model and decision rules defined, the full design space can be evaluated to find the optimal designs with flexible strategies. The model, Bayesian Network and decision rules were executed in MATLAB with the design space explored using a Monte Carlo approach and simulated annealing for optimization. Similar to Step 1, the initial capacity was optimized to understand the initial robust margins of the system. However, the system can now also execute decision rules decided by the Bayesian Network for expansion as defined in Step 3. The optimal design is summarized in the following table.

Table 6.4. ENPV of flexible decentralised design under uncertainty

NPV (S$ Million)	**Initial Capacity**						**Total Capacity (tpd)**
	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	
254	1400	900	850	800	550	500	5000

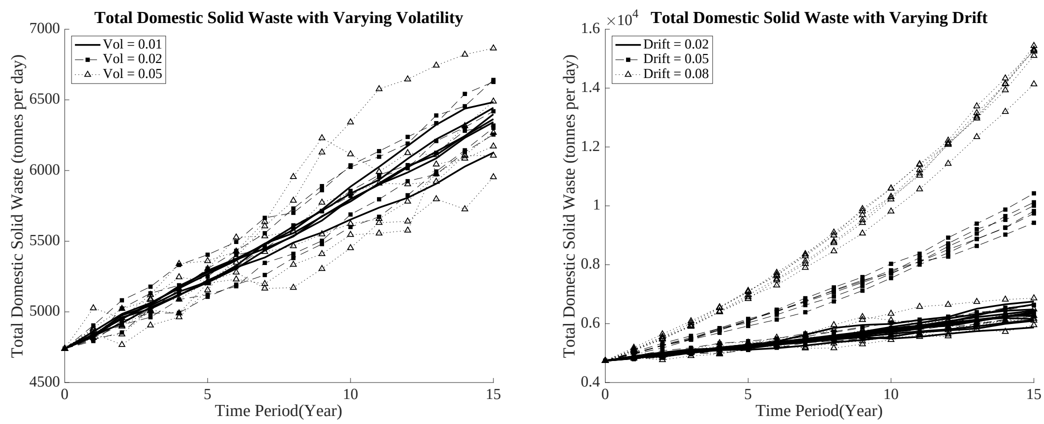
The ENPV of the flexible decentralised design is higher than the fixed decentralised design ENPV of S$250 million and fixed centralised design ENPV of S$242 million. The flexible centralised design gives an optimal ENPV of S$247 million. The total initial capacity of the flexible decentralised design is also lower than the fixed design which may indicate that it is better to defer initial capacity investment to allow for later expansion. The value of flexibility for the decentralised design is calculated by:

$$\begin{aligned} \text{VOF}_{\text{decentralised}} \quad &= \text{ENPV}_{\text{flexible}} - \text{ENPV}_{\text{fixed}} \\ &= 254 - 250 \\ &= \text{S\$4Million} \end{aligned}$$

These values are similar to those of Hu & Cardin (2015) and Ziqi (2017) where they modelled decision rules using IF statements. This gives confidence in the implementation of flexibility using Bayesian Networks moving forward.

6.1.6 Resilience Analysis

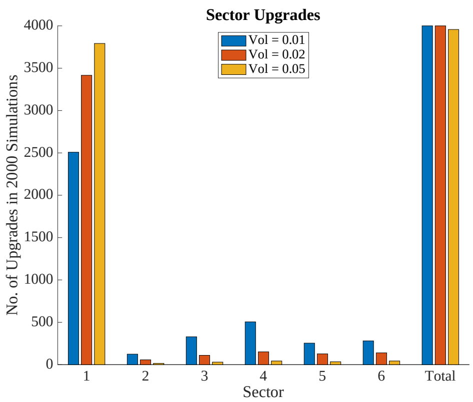
The key study of this work is to understand what and when to invest in as well as to gain insight into the robust and flexible strategies that can be used to maximize the system lifecycle value and make the system resilient to future uncertainties. This step thus varies the volatility and drift of the stochastic demand in order to assess the effects on the ENPV of the system and how it affects the investment strategies.



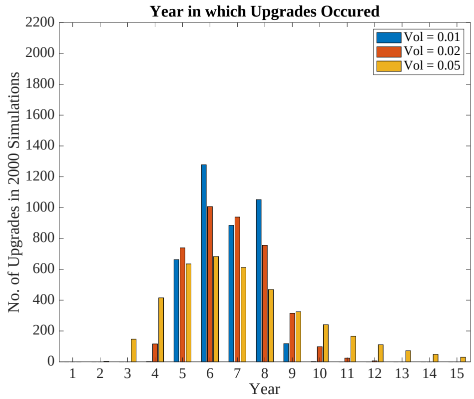
(a) Demand growth with varying volatility (b) Demand growth with varying drift

Figure 6.6. Demand growth over time

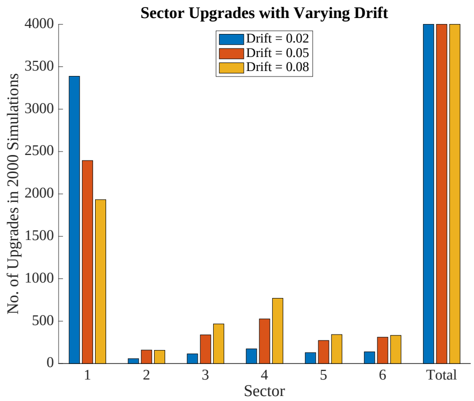
Figure 6.6.a illustrates the effect of varying the volatility whilst holding the drift to $\mu = 0.02$ on the total domestic solid waste projection. It is shown that



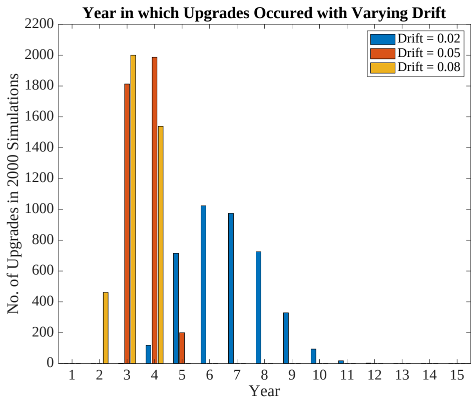
(a) Sector upgrades with varying volatility



(b) Timing of upgrades with varying volatility



(c) Sector upgrades with varying drift



(d) Timing of upgrades with varying drift

Figure 6.7. Effect of volatility and drift on upgrades

there is a wider "spread" of demands with increased volatility. The effect of varying drift with volatility kept to 0.02 is shown in Figure 6.6.b. With increasing drift, there is an increased rate of growth. The following analyses are based on the WTE system with optimized configurations as found in Design Space Optimisation unless stated otherwise. Although the previous step found the optimal configuration, it did not explicitly examine what sectors were upgraded over time. Thus, in order to satisfy the business requirements for this work, the investments over time are explored.

The effects of volatility and drift on the upgrades are shown in Figure 6.7. When varying the volatility through the simulations it can be seen from Figure 6.7.a that, although the total number of upgrades in the sectors are similar, the distribution of sectors that are upgraded are different. Sector 1, the main site, has the most number of expansions over 2000 simulations. The distribution over the other five sectors follow the distribution of transportation costs similarly and more upgrades are in sectors with higher transport costs. With increasing volatility, the system allocates more upgrades to S1 which is the centralised site. This is due to the condition in the Bayesian Network that all decentralised sectors need to exceed the threshold before decentralised expansion takes place. With increased volatility, there are large fluctuations in demand which causes the Bayesian Network to select an expansion but not every decentralised sector may simultaneously have the sufficient spike in demand to warrant decentralised expansion. In the simulations with lower volatility, the demand increases steadily such that the condition that all the sector exceeds the threshold happen at similar times.

There is also a narrower distribution of the investments over time with the simulations with a lower volatility having a lower variance as shown in Figure 6.7.b. This is expected due to the lower volatility having a smaller "spread" of demands. Furthermore, for all simulations, the upgrades do not start at year 1, and instead upgrades occur upon sufficient demand. The increased volatility also slightly reduces the total number of expansions and therefore the average number of expansions is also reduced with increasing volatility as shown in Table 6.5. This further means that the average number of years between expansions is longer due to the reduced number of expansions. This may be explained by noting that in the simulations, only volatility was varied and drift, the upwards trend, was held constant which means that inconsistent spikes of increased demand could also be followed by a dip in demand. Without a steady increase in demand, fewer simulations reached the expansion threshold and therefore a lower number of expansions occurred.

Table 6.5. Effect of volatility on average number of expansions

Volatility	**Average No. of Expansions**	**Average No. Years between Expansions**
0.01	2.00	1.93
0.02	2.00	1.93
0.05	1.98	2.00

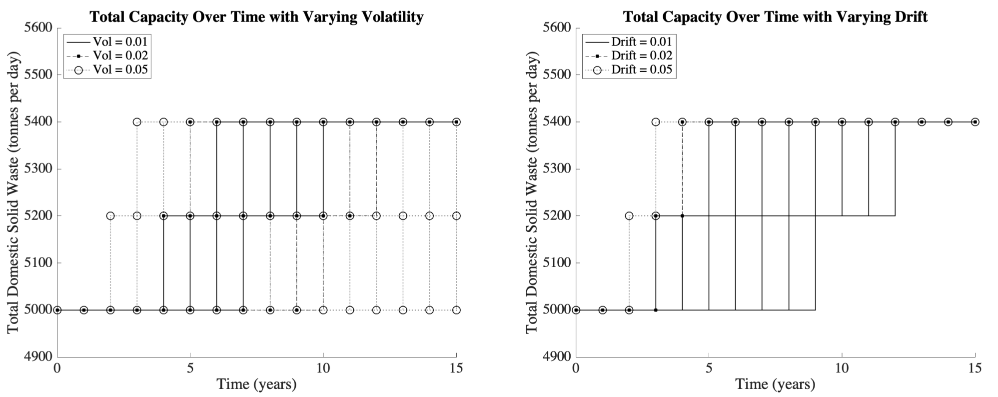
Figure 6.7.c and Figure 6.7.d show the effects of varying drift on the sector selection. Although, the total number of upgrades are similar, it can be seen that with increasing drift, there is more tendency to select decentralised sectors. The distribution of sectors again follow the transportation costs for each sector. The timing of upgrades is also earlier with increased drift due to the stronger upward

trend of the demand. The time between upgrades also increase with drift and at 0.08 drift as shown in Table 6.6 there is one year between the upgrades which is the minimum time allowable given that this simulation runs in annual intervals. The average number of expansions for all simulations are 2 since a maximum number of 2 upgrades were imposed. This implied that all simulations upgrade to the maximum allowed threshold.

Table 6.6. Effect of drift on average number of expansions

Drift	**Average No. of Expansions**	**Average No. Years between Expansions**
0.02	2.00	1.92
0.05	2.00	1.01
0.08	2.00	1.00

This is shown similarly by the increases in capacity as shown in Figure 6.8 where the set of solid lines indicate a volatility of 0.01, the square markers have a volatility of 0.02 and empty circles have a volatility of 0.05. It is seen that for low volatility, expansion occurs with a smaller spread of years in which expansion took place. As the volatility increases, the distribution of years in which expansion took place also increases. This is shown by the empty circle marker in more points of expansion. With increasing drift however, the upgrades occur earlier marked by the shift of lines to the left, similar to the results above.

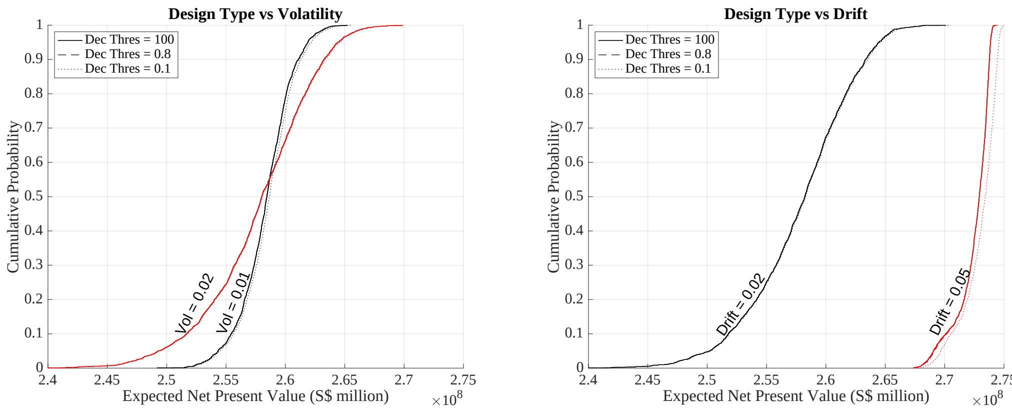


(a) Timing of investments and capacity of the system with volatility

(b) Timing of investments and capacity of the system with drift

Figure 6.8. Timing of investments and capacity with variations in demand

From the results above, a sense of which sectors and when to upgrade under different volatilities and drifts may be established. The centralised and decentralised design may also be compared through examining the ENPV of the designs. The model also incorporates a decentralization threshold which controls whether the expansion will occur in a decentralised or centralised manner. By setting this threshold high, the expansion only happens in a centralised manner. The effect of volatility and drift on design type are shown in Figure 6.9.



(a) Effect of volatility and decentralised threshold on ENPV

(b) Effect of drift and decentralised threshold on ENPV

Figure 6.9. Effect of volatility, drift and decentralised threshold on ENPV

It can be seen that for both volatility and drift plots, the lowest ENPV is with centralised expansion (left-most line) and the ENPV improves with decentralization. This is similar to the results found earlier. The effect of increasing volatility decreases the gradient of the cumulative probability plot due to the increased spread of demand projections and thus ENPVs. Drift increases the growth of demand which generates increasing revenue and thus shifts the plot to the right.

The conceptual requirements for this work suggests that there is a trade-off between the robustness and flexibility of the system. As such, the simulation is now ran for the decentralised system for a range of initial capacities and maximum number of upgrades to serve as proxies for each strategy respectively. The maximum capacity of the system was increased to 9000 tpd give a larger range of ENPVs and results. The results of this with the original demand data with drift = 0.0171 and volatility = 0.0203 is shown in Figure 6.10 and a top view given in Figure 6.11. The plots show consistent results to those in the optimisation step: the optimal initial capacity for the fixed, robust design (0 maximum number of expansions) is around 5200 tpd (Table 6.3) and for the flexible case is around 5000 tpd with one expansion (Table 6.4). The ENPV results are also similar and indeed it seems that the optimal configuration, by seeing where there is overall the darkest red colour, is to have the flexible strategy with one expansion. This is due to the demand profile distribution, which is shown in Figure 6.12. Having the configurations as found per the optimisations allows the system to capture more of this demand profile. The high count at the beginning of the distribution around 4700 tpd is due to the simulations starting at 4740 tpd.

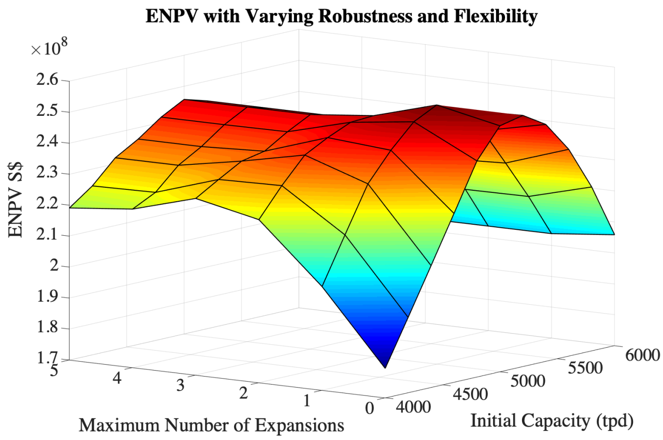


Figure 6.10. Surface plot with initial capacity against maximum number of upgrades

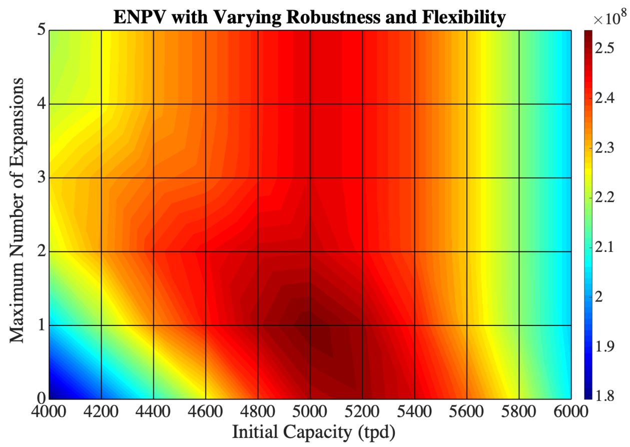


Figure 6.11. Top view of plot with initial capacity against maximum number of upgrades

On the left side of Figure 6.11, where there is low initial capacity, there is a low ENPV due to the inability to capture the full demand. This improves with the number of expansions but as indicated on the top left corner of Figure 6.11, the ENPV dips again showing that too many upgrades negates any increased

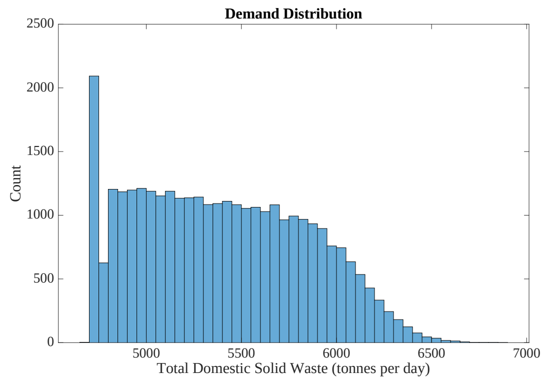


Figure 6.12. Demand distribution for Waste-to-Energy system

revenue from increased demand. This is the case in general, and the ENPV remains constant for higher numbers of maximum upgrades which highlights that the criteria to upgrade is not met i.e there is insufficient demand to warrant upgrade leading to a plateau in ENPV. On the right hand side of Figure 6.11 where there is a high initial capacity, the ENPV is also lower since there is insufficient demand to meet such a high capacity. This is similar to the Iridium satellite case where a constellation of satellites were launched but inadequate demand meant that initial setup costs were not recovered and resulted in financial loss. The simulations with no increase in capacity over time are unable to take advantage of increased demand over time and therefore give a lower ENPV. These insights are summarised in Figure 6.13.

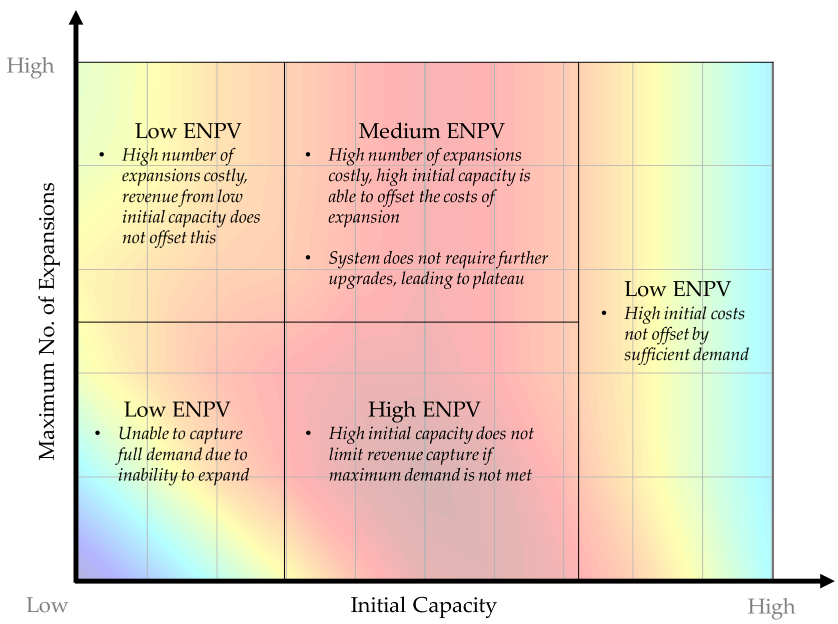


Figure 6.13. Descriptions on different region of the ENPV surface

The effects of changing volatility and drift on the ENPV can be visualised from Figure 6.14 and Figure 6.15 where the ENPV surface and the top view is put side by side. For the volatility set of results, the drift has been held constant at 0.02 and mapped to a colour map with a maximum and minimum set to 1.7×10^8 and 2.6×10^8 respectively for comparison. When varying drift, the volatility was held constant at 0.02 and mapped to a colour map with a maximum and minimum set to 1.7×10^8 and 3.2×10^8 respectively for comparison.

From Figure 6.14, the effect of volatility is shown and the increase in volatility decreases the ENPV. This is shown by the flattening of the surface and the slight change in colour seen from the top view. The higher volatilities may be more prone to exceeding the maximum capacities due to the higher spread of demand, resulting in reduced ENPV. The shape of the surface is similar, however, and volatility does not seem to change the optimal configuration of having around 5000 tpd initial capacity with 1 expansion.

The drift, on the other hand, has a much bigger impact, as shown in Figure 6.15. With increasing drift, the maximum ENPV shift towards the upper right. This is as expected since drift increases the growth rate of demand and thus more upgrades are needed to suffice demand. Furthermore, the right hand side of the plots originally showed a low ENPV from the insufficient demand. This now yields an improved ENPV due to the increased demand. From the results in the first instance the better ENPVs result from having some initial capacity with some upgrades and thus a hybrid of robustness and flexibility as shown by all of the surfaces. Furthermore, while the ENPV is clearly a function of capacity and thus demand, whether a purely robust or flexible strategy should be employed must depend on some other factor. Attention now turns to the costs for the system and specifically the initial setup cost and the cost of each expansion. The ratio between the expansion cost and the initial installation cost is varied and shown in Figure 6.16. With a relatively low cost ratio, where the expansion cost is less compared to installation costs, it is seen that a flexible strategy again yields the highest ENPV. The low cost of expansion does not negate significantly the benefit gained in extra capacity and thus the flexible strategy should be used. However, as the cost of expansion increases, the extra revenue does not offset the expansion costs and the surface starts to change shape. In the bottom plot, where the cost ratio is 0.25, or the expansion cost is 25% of the initial costs, a robust strategy yields a higher ENPVs. It should further be noted that the robust set of ENPVs, where maximum number of upgrades is 0, obviously does not change. In these cases, the cost of expansion is too high and a robust strategy should be employed.

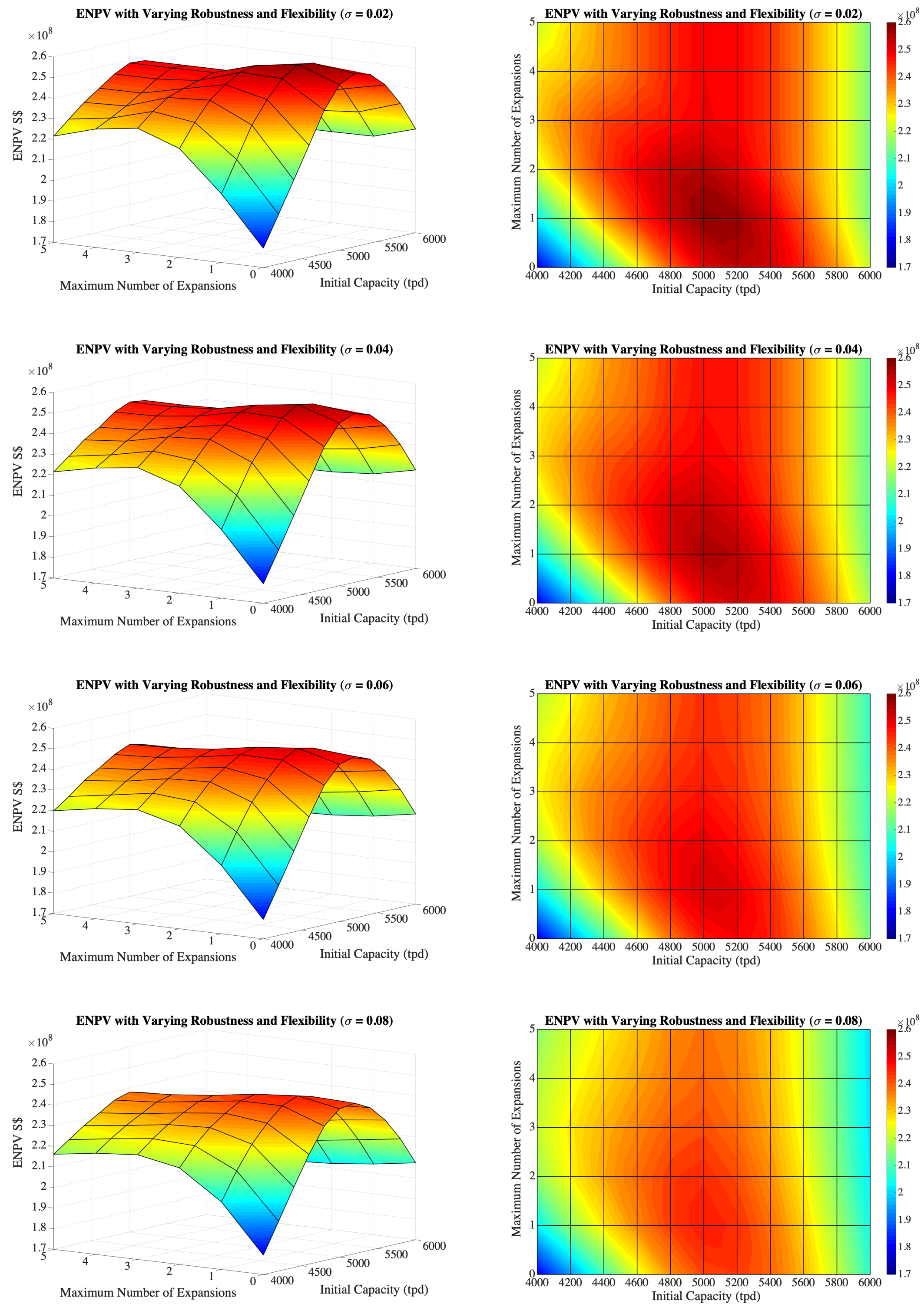


Figure 6.14. Effect of volatility on ENPV surface against initial capacity and maximum number of upgrades

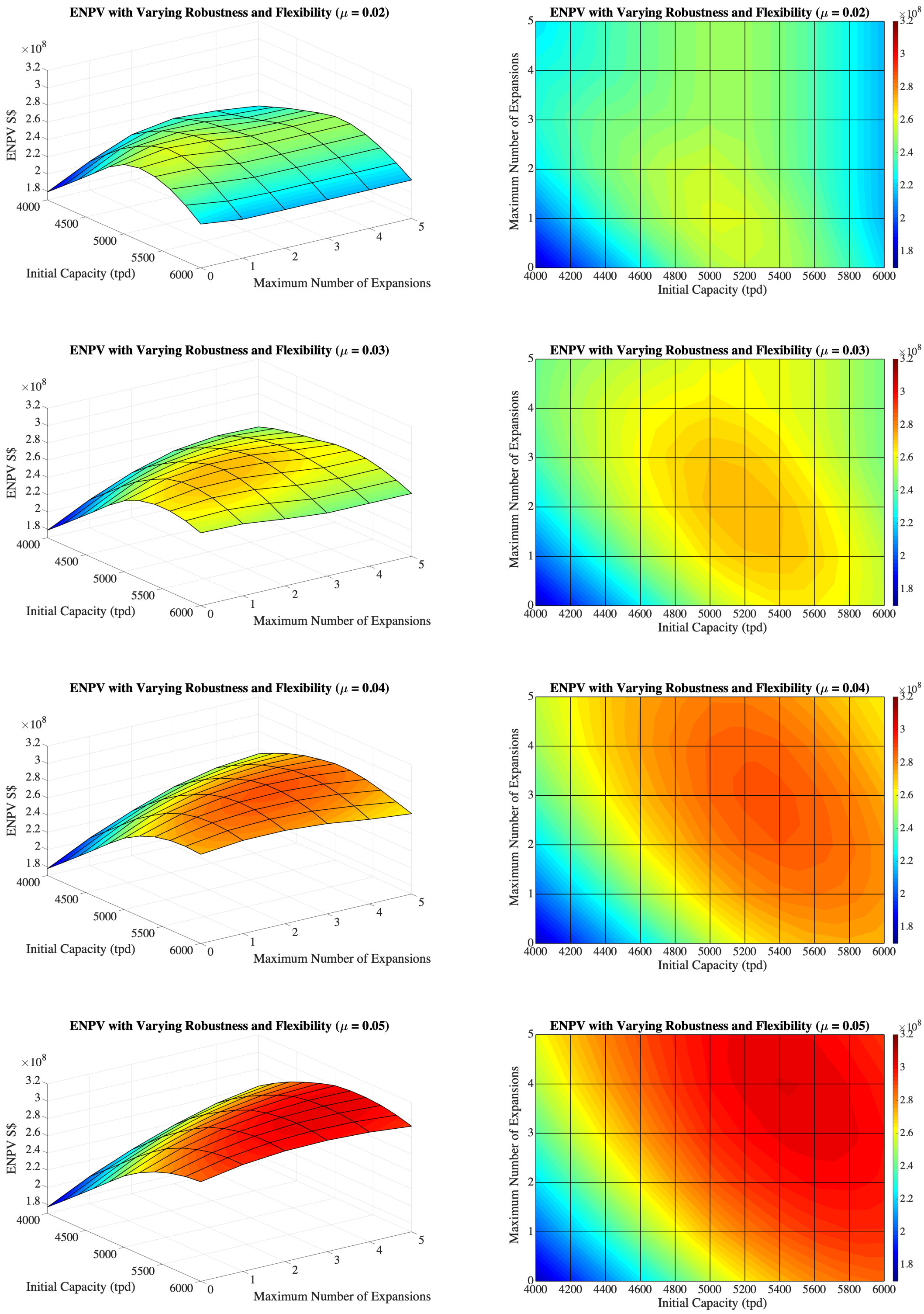


Figure 6.15. Effect of drift on ENPV surface against initial capacity and maximum number of upgrades

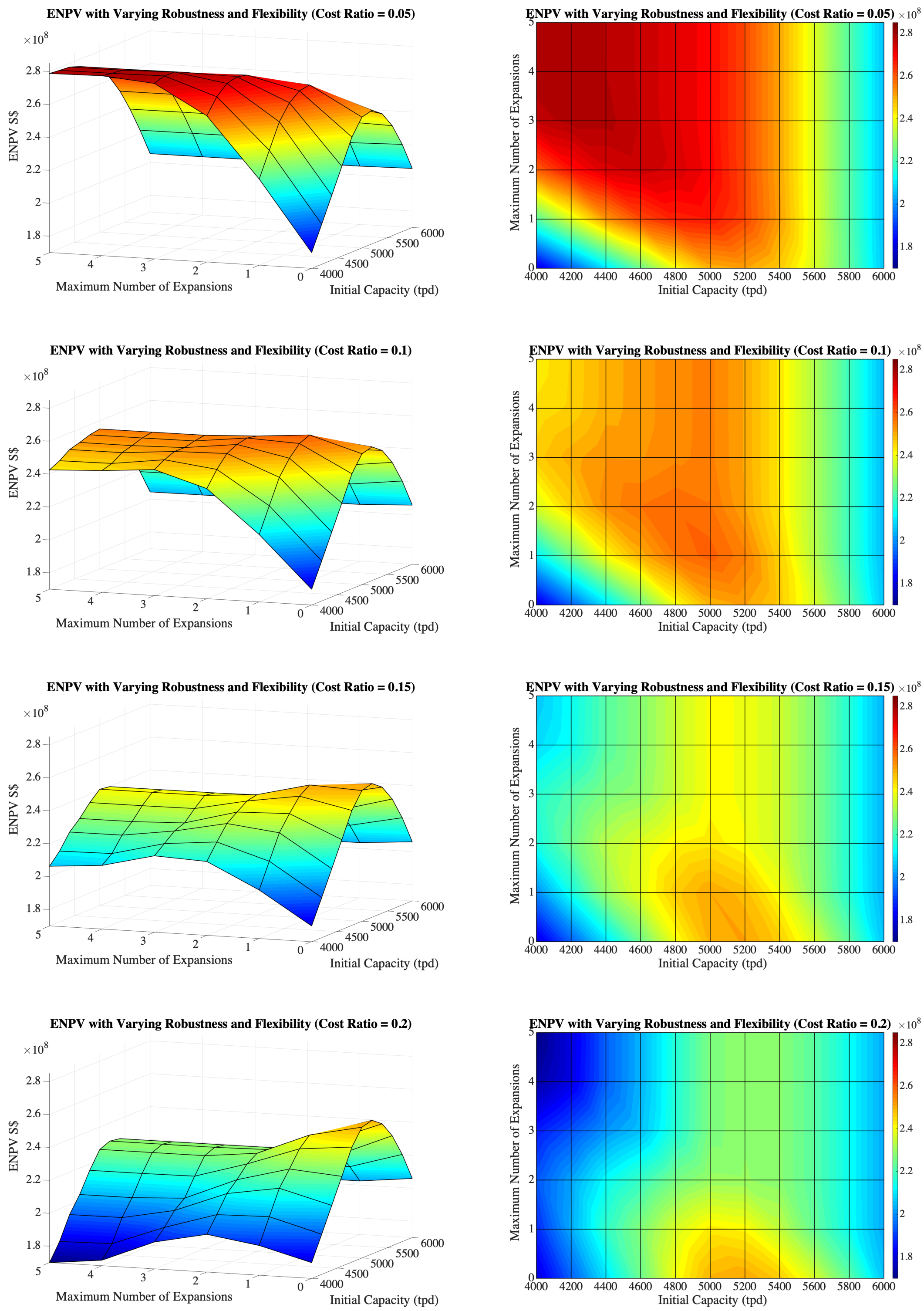


Figure 6.16. Effect of expansion cost on ENPV surface against initial capacity and maximum number of upgrades

6.1.7 Discussion & Summary

This first case study applies the support method for designing resilient engineering infrastructure systems to a Waste-to-Energy system in Singapore and investigates the role of robust and flexible strategies in maximising the system lifecycle value as measured by ENPV. This builds on work by Hu & Cardin (2015); Ziqi (2017) by further including Bayesian Networks to model decision rules as well as investigating how resilience can be achieved. Furthermore, this case acts as a verification of the support method by benchmarking results to previous work, giving confidence moving forward in applications with industry.

Following the framework as prescribed in Chapter 5, the first step is to develop the initial robust model with no upgrades so that there is a benchmark for comparison. After projecting some uncertainty, flexibility was implemented through the use of Bayesian Networks to select sites for decentralised expansion. The results show that a decentralised design performed better than a centralised design and flexibility shows increased value compared to a fixed robust design. However, when the system is allowed to upgrade too often, the costs of implementation negates the revenue increase. The better design is to have an initial capacity within the region of projected demand and with a few expansions such that there is less restriction on the demand. The Bayesian Network shows promise in implementing decision rules, giving similar results to previous studies, and should be considered further where decisions need to be more complex, perhaps involving qualitative and quantitative data. This gives confidence for the second case study with industrial sponsors BT in the next section.

This work further contributes a resilience analysis whereby the sectors for expansion and the timing of upgrades with varying volatility and drift were first explored. Increased volatility gave a tendency to upgrade in the main site compared to the decentralised site since the spread and fluctuations in demand meant that thresholds in the decentralised sites were not triggered. With increasing drift, the opposite was seen, and there were more expansions in the decentralised sites. The increased drift also meant earlier investments with higher ENPVs due to the extra demand while the increase in volatility gave a wider spread of years in which investments were made.

The conceptual requirements necessitated a study of the trade-offs between robustness and flexibility. The simulations were ran with variations in initial capacity and maximum number of upgrades serving as proxies for robustness and flexibility respectively. The resulting surface matched the earlier optimisations suggesting the better design is to have an initial capacity of 5000 tpd with 1 expansion. It is shown that by having a low initial capacity and/or meeting the demand on the system through a high number of expansions yields a low ENPV. This is due to each expansion incurring a cost which negates the benefit in allowing for the flexibility. Similarly, the value of flexibility is also negated where there is a high initial capacity and a high number of expansions. On the other hand, having too high an initial capacity without sufficient demand was also detrimental to ENPV. Increasing volatility generally made the system perform worse since not all demand could be converted to revenue, while increased drift emphasised the added value of flexibility and that with a high drift there should be more flexibility to satisfy demand.

While the model has been able to find the robust and flexible strategies for optimising ENPV – an initial capacity of 5000 tpd with 1 expansion in the decentralised case – it was intriguing whether flexible strategies were always necessary. Since in all of the simulations with the initial configurations have suggested that the system would perform better with some flexibility, the choice between the design strategies must further rely on some other factor. Given that the system is measured by ENPV, the effects of installation costs and upgrade costs were considered. Indeed, it is seen that where expansion cost is low compared to the initial cost, the flexible strategy should clearly be deployed. On the flip side, if the expansion costs are high, however, the robust strategy, with no upgrades, would yield a higher ENPV. Concluding this first application:

- Resilient design strategies, robustness and flexibility, were found by optimising the ENPV of the system
- Bayesian Networks have been found to be adept in modelling decision rules
- Model is able to show when and what technology to upgrade over time
- Optimal robustness and flexibility are more heavily influenced by the drift of the demand than volatility
- Cost of expansions are critical in flipping the system between a purely robust system and a hybrid of both strategies

6.2 Telecommunications Infrastructure Investment with BT

The support method proposed in Chapter 5 is now implemented for telecommunications infrastructure investment with BT. This case follows the same framework as before but with an emphasis on understanding how the model may be received and delivered into industry. In this respect, the major challenges involved extracting the Bayesian Network structure and obtaining probabilistic data from industry experts as detailed in Chapter 5. Once the Bayesian Network was extracted and the dependencies which may influence the decision making process were captured, a NPV model was constructed so that similar analyses to the WTE system could be performed. The main design choices were the types of technology to be deployed in each region. In contrast to the previous case, these choices are now discrete options with different characteristics as opposed to unit upgrades as before. The initial technology option and thus traffic capacity served for initial robust model analysis and the Bayesian Network was then used to decide which technology, if any, the region should upgrade to given uncertainties in the region. Here, building on the WTE case, the Bayesian Network can both select increases in capacity through throttling as well as having the option to switch technologies. The resilience of the system under different design strategies were then assessed by varying volatility and drift of the demand over different timescales and costs.

6.2.1 Background of Case Study

BT is the largest provider of consumer fixed-line voice, broadband services and mobile in the UK (BT, 2018a). It traces its origins back to the Electric Telegraph Company, introduced in 1846, making it the world's oldest telecommunications company (BT, 2018b). Through a series of mergers, the Electric Telegraph Company was eventually transferred to the Post Office, a government department at the time and following the Post Office Act, 1969, the Post Office became a public corporation with the telecommunications arm becoming British Telecom in 1980. This went on to be privatised in 1984, and traded as BT in 1991.

At the time of this work, the roll out of "superfast" broadband, providing download speeds greater than 24Mbits/s, has been a priority to both the government and to BT so that the UK internet infrastructure remains competitive on the global stage. In the UK, broadband can be delivered through two main infrastructure systems: fixed line, which uses a network of copper and optical fibres, and wireless, which uses radio waves transmitted through satellite, WiFi or mobile technology (3G/4G/5G). In order to reduce complexity of the problem and satisfy stakeholder interests, this thesis focuses only on fixed line infrastructure at this stage. The fixed line network comprises a core network which forms the backbone of the communications network and carries different services such as voice or data at high capacity across the UK using fibre optics. The core is then connected to the “access network” which constitutes the connections from the exchanges, which houses electronic equipment to connect telephone calls, to the green road-side cabinets, also known as primary connection points (PCP), and then on to each household.

BT’s access network has traditionally used copper lines to deliver data throughout the entire network. More recently, in an effort to improve the network and deliver “superfast” broadband, new fibre technologies, under the Next Generation Access (NGA) scheme, have been introduced (Broadband Delivery UK, 2018). Specifically, the NGA scheme upgrades various parts of the access network from copper to fibre and comprises of the technology options: fibre-to-the-cabinet (FTTC), G.Fast and fibre-to-the-premises (FTTP) as illustrated in Figure 6.17.

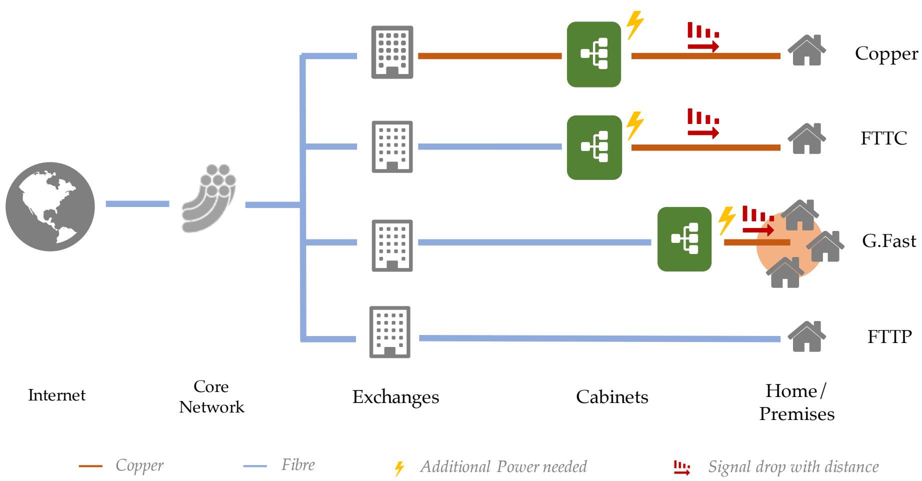


Figure 6.17. Illustration of different technology options available with the Next Generation Access (NGA) Scheme

Each technology has particular characteristics and performances. Copper typically stretches from the exchange in bundles of up to 4800 pairs via underground ducts to roadside cabinets. These are then connected to distribution points which are situated above ground at the top of telephone poles or within larger office buildings. For the distribution points on top of poles, these are then connected to each home via a drop-wire strung between pole and the home

(Houses of Parliament, 2017). Copper networks normally serve Asymmetric Digital Subscriber Line (ADSL) technology which come in two forms: ADSL1 which is capable of a maximum speed of around 8Mbit/s and ADSL2+ with a maximum of around 24Mbit/s (Ofcom, 2015). However, a characteristic of copper networks is that the signal is constrained by the distance from the exchange and the signal quality delivered decreases with increasing distance. This leads to limited download and upload speeds for households far from the exchanges.

In contrast, for fibre optics, the signal does not degrade significantly with distance which, coupled with the much larger capacity of fibre optics, makes it an attractive upgrade option. Fibre-to-the-cabinet (FTTC) uses fibre optics to connect exchanges to the street cabinets and copper from the cabinet to the household. While the signal is improved considerably with a potential maximum download speed of 76 Mbit/s, having copper for the final link still limits speeds for those located far away from the cabinet. G.Fast is a relatively new technology and is similar to FTTC in that fibre is laid down from the exchange to the cabinet and copper from cabinet to the house, but the distribution point is situated much closer to the home, typically in the tens of meters. The length of copper is therefore reduced and G.Fast lines can reach an increased maximum speed of 330 Mbit/s (Openreach, 2018c). Speeds in this range and those generally over 100 Mbit/s are termed "ultrafast" broadband. For both FTTC and G.Fast, there is an additional need for extra electricity and installations to the cabinet due to the final copper link. The final option available is fibre-to-the-premise (FTTP) where there is fibre all the way from exchange to the house or premise without necessarily needing to go via a cabinet. The signal does not degrade with distance nor needs an extra electricity supply and can provide broadband speeds of up to 1 Gbit/s, branded as "hyperfast" broadband (Broadband.co.uk, 2018).

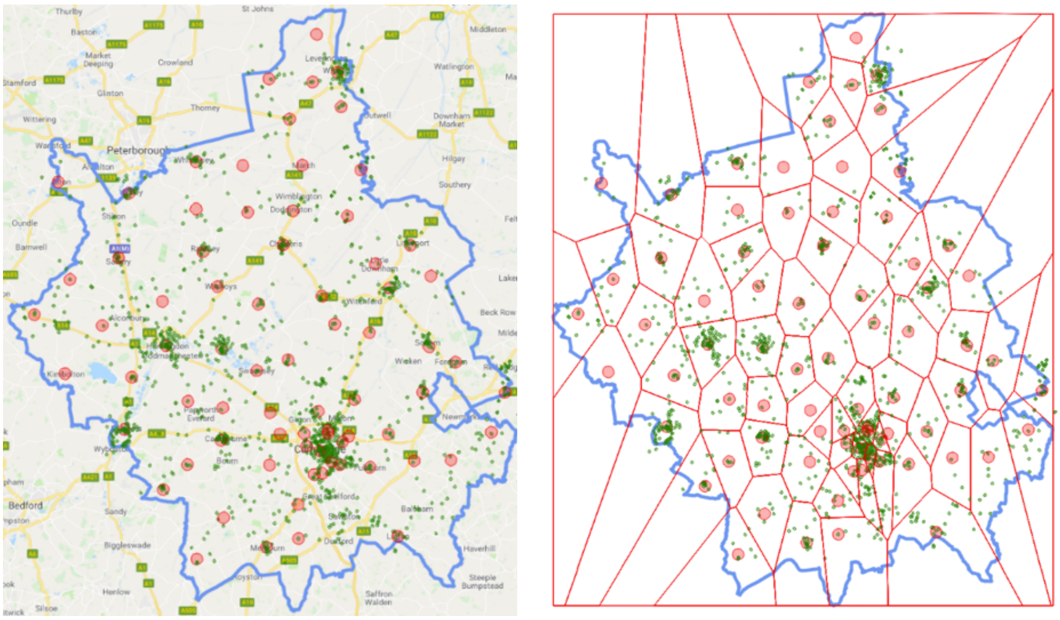
BT's roll out of the NGA network was initially announced in July 2008 (Wearden, 2008) and aimed to connect around 45% of the homes, or around 10 million homes, through NGA technologies within four years through a £1.4 billion investment. This was then further extended in 2010 to cover two thirds of UK households by 2015 and forecast to cost £2.5 billion (Frontier Economics, 2015). By May 2014, BT announced that it had largely completed this roll out of the NGA network covering the target of two thirds of UK households and further rollout of the NGA network is now being funded by Broadband Delivery UK (BDUK) through a public subsidy of approximately £1.7 billion split into three phases (Broadband Delivery UK, 2015):

- Provide superfast broadband coverage to 90% of UK homes by 2016 and standard broadband (> 2Mbit/s) for all homes.
- Provide superfast broadband coverage to 95% of UK homes by 2017.
- Extend superfast broadband coverage beyond 95% (in planning)

The UK government's broadband programme also aims to comply to the goals of the Digital Agenda for Europe where the entire EU is to be covered by broadband above 30Mbit/s by 2020, internet speeds of 100 Mbit/s are to be installed into half of all households by 2020, and 33% of small and medium-sized enterprises are to be able to make online sales by 2015. To meet these targets, a substantial amount of planning and consideration is needed. In particular, characteristically of infrastructure systems, changing the system once installed is difficult. In BT's case, once the lines are laid underground, replacements and modifications would require re-digging the lines, making rectification costly and time consuming.

The task in this case study is therefore to understand the factors that affect the decisions for technology deployment over different regions of the UK and understand the optimal upgrade process with a long term, strategic view. With such a challenge, resilience plays a critical role in understanding the initial robust capacities that the network should have and when the network should be upgraded to ensure all targets are met, customers are satisfied and to make the upgrade process efficient considering volatilities in demand. While the whole network could be upgraded straight to FTTP to provide the best customer experience, the relatively higher installation costs also bring with it associated risks. For example, de Weck demonstrated that unmet demand forecasts led to the bankruptcy of the Iridium satellites and that a phased approach may have saved USD$2 billion. As such, FTTC and G.Fast represent intelligent intermediary technologies which can phase this upgrade process and, instead of the whole network bring pushed to fibre simultaneously, it can be upgraded when demand necessitates.

The support method is first demonstrated for this study over Cambridgeshire and extension for the whole of the UK is left as an exercise for the reader. Approximate postcode locations of 75 exchanges and 1327 cabinets (see Appendix B.1 & B.2) were gathered from public sources (Magenta Systems, 2018; Sam Knows, 2018) and represented by red and green spots respectively in Figure 6.18.



(a) Outline of Cambridgeshire

(b) Voronoi diagram with exchanges as seed locations

Figure 6.18. Exchange (red spots) and cabinet (green spots) locations in Cambridgeshire (blue outline)

In Figure 6.18.a, the Cambridgeshire outline, exchange and cabinet locations superimposed onto Google Maps using WGS84 coordinates and the *gmplot* library in Python. A Voronoi diagram (Figure 6.18.b) is then generated using the exchanges as seed locations to give polygons which show the closest seed for any point. In other words, for any point in the map, the closest exchange is found by the exchange in the respective enclosing polygon. To bound the diagram in a square box, the seeds were mirrored horizontally and vertically. Voronoi diagrams have been used in many applications such as astronomy, cell growth, as well as urban planning (Okabe *et al.*, 2009) and have also found use in telecommunications to represent area coverage (Portela & Alencar, 2008). This has further been confirmed as appropriate by BT researchers and also used similarly in BT's internal models. Each exchange can serve multiple technologies and each line to every individual premise could be modelled. However, this data, for all lines to every house, has not yet been feasible to source given the timescales for this work and therefore each exchange in each area is assumed to only serve one technology to every premise.

Further data that has been sourced include: the number of residential & non-residential customers served per exchange, FTTC & FTTP availability and the presence of competing service provider, Virgin Media, in the area. From the postcode locations, distances in each of the line sections from exchange to cabinet, from cabinet to house and the total distance can be calculated and averaged as shown in Figure 6.19.

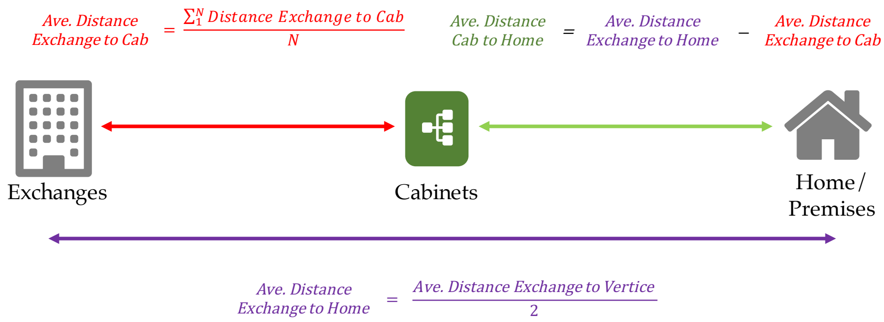


Figure 6.19. Calculation of distances for different sections from exchange to premise

The average distance from the exchange to the cabinet in each area is calculated by transforming postcode data to longitudes and latitudes before using the Haversine Formula to determine the great-circle distance between two points. The distribution of houses have been assumed to be uniform and therefore it is assumed that the average distance from the exchange to each house lies halfway between the average distance from the exchange to each vertex of the Voronoi diagram as shown in Figure 6.20. The red and green markers represent exchanges and cabinets respectively. The arrows show the distance from the exchange to the vertex and therefore, in Figure 6.20, the average distance is taken of these five distances and divided by two. By knowing these two distances, the final length of the line, from cabinet to home, is a subtraction of the first two lengths.

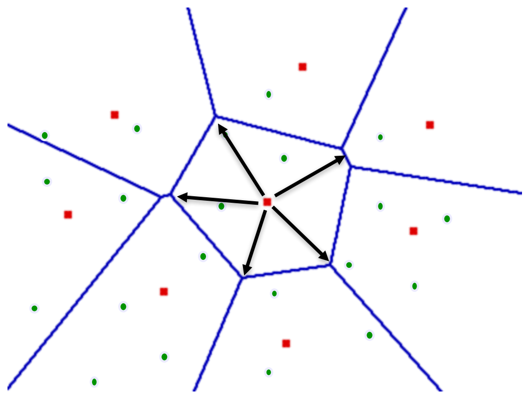


Figure 6.20. Illustration of Voronoi diagram

6.2.2 Initial Robust Design

With the exchanges and preliminaries defined, the first step of the support method can be conducted to give benchmark NPV results where the technology is fixed over time. The NPV, similarly to previous case study, is given by

$$NPV = -C^0(x) + \sum_{t=1}^{T} \left(\frac{1}{1+\lambda}\right)^t \left(R^t(x, d^t) - C^t(x)\right) \tag{6.10}$$

where x is the installed technology capacity, d^t is the demand in traffic at time t, λ is the discount cost, C^0 is the initial installation cost, and R^t and C^t is the revenue and costs at time respectively. The revenue and costs data for each technology has been sourced from Openreach (2011; 2017a; 2017b; 2018a; 2018b; 2018d), BT's maintenance and provision arm, and wholesale prices for each connection are presented in Table 6.7.

Table 6.7. Revenues and costings for NGA technologies

	Copper (£)	**FTTC (£)**	**G.Fast (£)**	**FTTP (£)**
Installation Cost	0.00	227.99 per 100m	227.99 per 100m	227.99 per 100m
Maintenance Cost	54.32	48.00	48.00	48.00
Throttle Cost	20.00	20.00	20.00	20.00
Customer connection revenue	100.10	92.00	99.00	500.00
Customer rental revenue	52.98	119.40	119.40	960.00

The main costs are assumed to result from the installation costs, maintenance and change in throttling. Installation costs result from the assumption that the provision of new lines require engineers to lay new lines or replace the existing connections. It is assumed that the network is currently copper and that no further provisions are necessary, negating the copper installation cost. The installation costs for the other technologies are taken from the cost to recover a heavy cable per 100 metres from the Openreach catalogue. In the case of FTTC and G.Fast, this cost is then multiplied by the distance from the exchange to cabinet since the rest of the connection, from cabinet to home is assumed to remain as copper. For FTTP, it is assumed that there needs to be work done for the whole line from exchange to home and so, the total distance is multiplied by the installation cost. Openreach currently offers four maintenance levels: from level 1, which aims to clear problems by 23:59 the day after next, to level 4, which aims to clear within 6 hours . The maintenance cost is taken from the annual price of the highest maintenance level, Service Maintenance Level 4, for each technology respectively . It is assumed that this service is not subsidised so that the maximum cost associated with maintenance should be at least covered by the price of these packages. A throttling system is included in the NPV calculations to reflect that software, or otherwise, can regulate the speeds of each connection. As such, a number of broadband packages can be available to customers and, even if fibre is deployed, the customer can select a broadband speed that suits their needs as opposed to the full installation capacity. Thus, the throttle upgrade cost is assumed to be constant across all packages, if involving some software solution. The revenue, accounts for a customer connection fee and annual rental. More specifically, the customer rental revenue is calculated from either the demand or the installed capacity, whichever is lower. This reflects the situation where there may be a demand for faster broadband but the higher capacity technology is not available. It may also be the case that, on the flip side, the customers do not need as high a capacity as the installed capacity. The NPV for each exchange area is calculated with the above numbers and multiplied by the number of customers in the area.

The growth in demand is projected from the historical average broadband download speeds which has been obtained for 2009 – 2017 from Ofcom, UK's communications services regulator (Ofcom, 2013). This is shown in the solid line in Figure 6.21. Using a similar projection as before, the demand growth is calculated from

$$S^t = S^{t-1}(1-\mu) \tag{6.11}$$

This gives an average year on year growth of 36% year resulting in projected download requirements of 4652.92 Mbit/s in 15 years, or by 2032. This is substantially more than the technology capabilities available today and those considered in this work. Running simulations with these numbers lead to maximum NPVs where all the exchanges are upgraded to FTTP. Furthermore, there has been a significant push in recent years from the announcement of the NGA scheme in 2008 to upgrade the telecommunications networks, leading to this growth trend and this may or may not be sustainable for a further 15 years once the majority of lines are upgraded. The following simulations therefore consider a year on year growth of 13% with Year 0 at 46.2 Mbit/s as shown in Figure 6.21 and documented in the Appendix B.3.

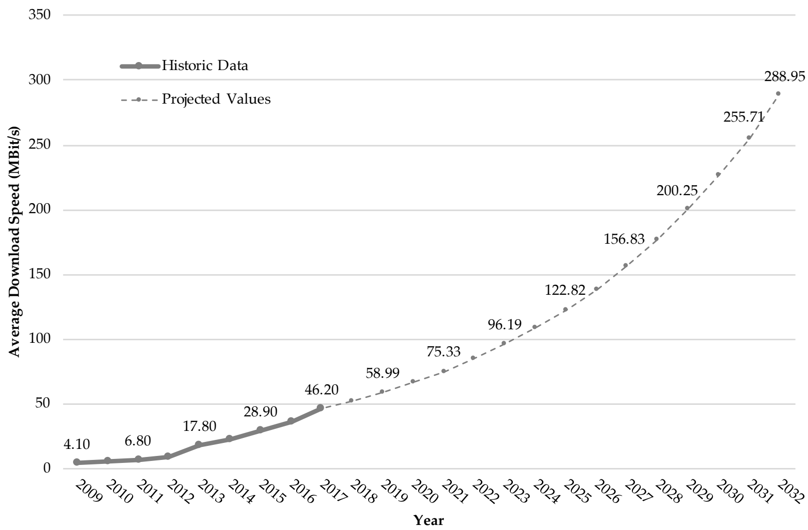


Figure 6.21. Projection of average download speeds for 15 year time horizon

Table 6.8. NPVs for Cambridge with different initial technologies, fixed over time

Technology	**Throttle**	**Capacity (Mbit/s)**	**Total NPV (£)**
Copper	25%	6	76,475,448.37
	50%	12	605,607,810.17
	75%	18	1,487,495,079.84
	Max	24	2,722,137,257.37
FTTC	25%	19	214,493,121.38
	50%	38	3,990,728,417.65
	75%	57	10,284,453,911.44
	Max	76	17,141,073,231.42
G.Fast	25%	82.5	9,578,642,601.03
	50%	165	18,030,779,736.23
	75%	247.5	22,671,712,698.34
	Max	330	24,906,621,693.86
FTTP	25%	256	25,650,639,407.55
	50%	512	25,650,639,407.55
	75%	768	25,650,639,407.55
	Max	1024	25,650,639,407.55

The simulation is now ran for all 75 exchanges for 15 year period with a discount rate of 10% and throttle sizes of 25%. All possible technology options and the NPV results for the whole of Cambridgeshire per given technology are shown in Table 6.8. As expected, as capacity increases, so does the NPV until a plateau for FTTP. This is because the maximum projected value is 288.95Mbit/s where an upgrade to G.Fast would suffice. Since the revenue is taken to be a function of demand or maximum capacity of the installed, whichever is lower, a further upgrade to FTTP would not bring further benefit. The following plots in Figure 6.22 shows NPV results for exchanges in Cambridgeshire initialised to the Copper, FTTC, G.Fast and FTTP at full capacities. The colour scale is normalised across all plots to show the relative changes in NPV with differing technologies. It is shown that FTTP generally gives a better NPV since it is able to convert all the projected demand to revenue. Lower capacity technologies, such as copper, only capture a small portion of this demand and the NPV is thus lower. Areas with more numbers of customers served also have a higher NPV with the highest NPVs found in the Cambridge city centre area.

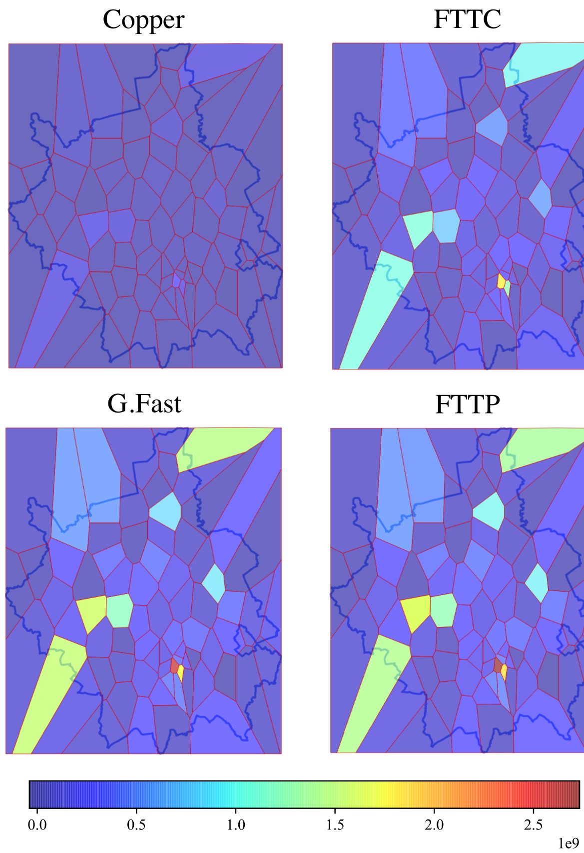


Figure 6.22. NPV results over Cambridgeshire with initial technologies: Copper, FTTC, G.Fast, FTTP

The change in NPVs for each specific area can be examined in more detail as illustrated in Figure 6.24 which shows a grid of each exchange and each technology combination, coloured by NPV. It is seen, similar to the aggregate view given by Table 6.8, that the NPVs for the exchanges seem to rise to around the maximum capacity of G.Fast before plateauing with FTTP after which there is no extra revenue generated from the higher capacity.

It can be seen that, generally, the technologies with higher capacity and the areas with the highest number of customers generate the highest NPVs. However, upon closer inspection, it was found that the distance in each exchange area also plays a role in determining the fixed technologies which give the maximum NPVs. It can be seen that for areas where the total distance from exchange to the premise is greater than around 4km, G.Fast technology would actually result in a greater NPV than all other technologies. This is visualised on the following overlay in Figure 6.23 showing the technology choices which maximises NPV in each area.

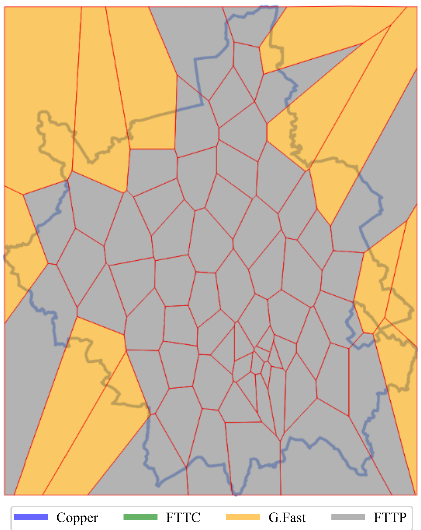


Figure 6.23. Fixed technologies which maximise NPV for Cambridgeshire

This results from FTTP requiring work on the whole line, from exchange to the home, leading to higher installation costs for areas with large distances. For G.Fast only the line from exchange to cabinet needs to be replaced and thus for areas with large distances, the installation costs would be relatively cheaper. The total NPV with the optimal technologies in each region is £25.9×10^9. It should be noted that it is an inflated figure due to the limited NPV model and cost information. However, these figures can be refined with industrial input in future work and the model is used to demonstrate the utility of the model.

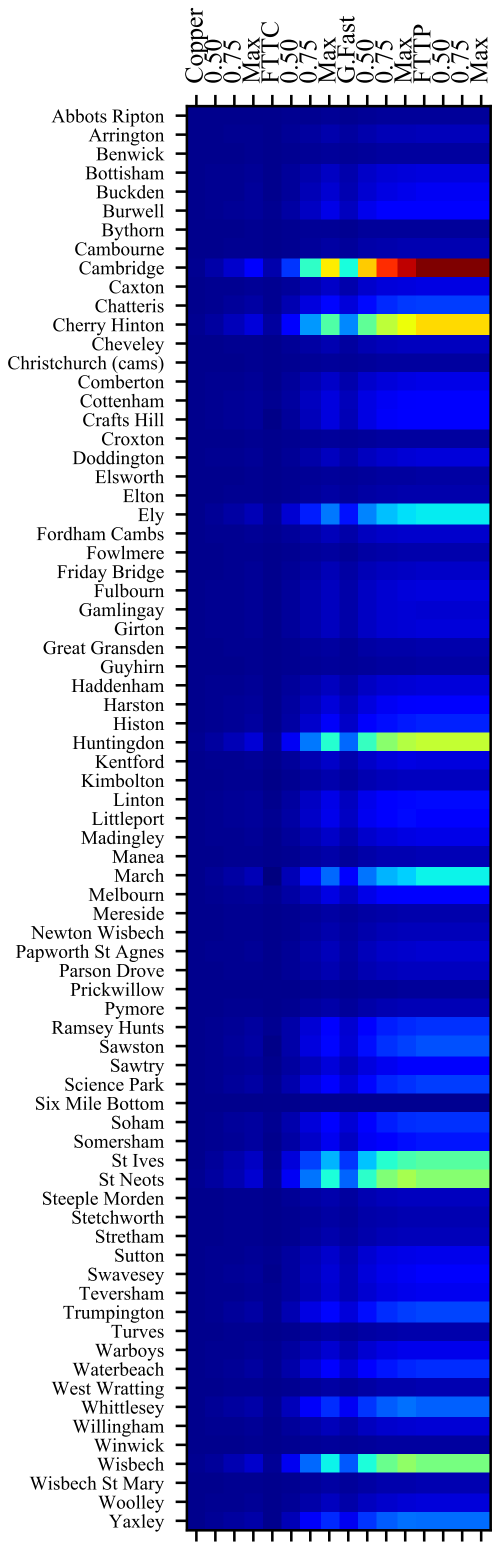


Figure 6.24. Grid representing NPVs for each area in Cambridgeshire initialised to each technology

6.2.3 Uncertainty Recognition

This work focuses on understanding the strategic view for infrastructure design for resilience, and therefore the main uncertainty of interest is the evolution of demand over time. As such, the average download speed growth is taken to be a proxy of demand and day to day resiliency to threats such as maintaining uptime in the face of natural disasters, terrorism, or system failure are not considered. Uncertainty is now introduced through geometric Brownian motion to model the growth in average download speeds using

$$dS_i^t = \mu S_i^t dt + \sigma S_i^t dW_t \tag{6.12}$$

where S_i^t is the download speed at time t and simulation run i, μ is the drift or growth trend and σ is the volatility taken as the standard deviation of annualised growth. The Wiener process is represented as W_t. Geometric Brownian motion represents a continuous-time stochastic process where the logarithm of the random variable follows a Brownian motion with drift and is typically used in financial models. Values of 0.122 and 0.03 were used for μ and σ respectively to fit projections to the benchmark model (Liden, 2018). Sample paths are shown below for 50 simulation runs.

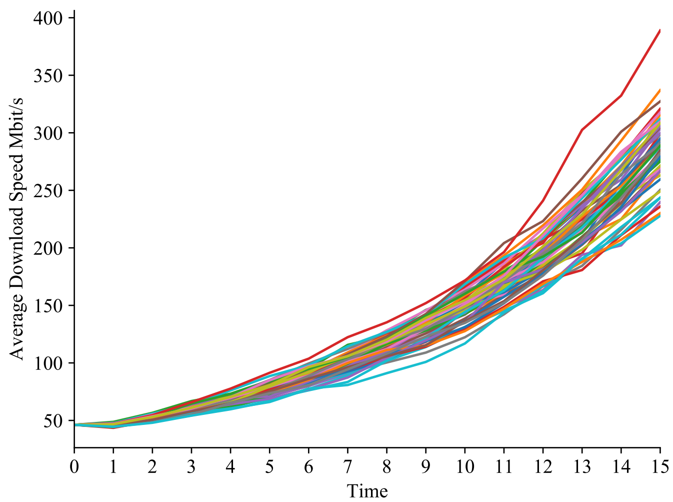


Figure 6.25. Demand paths of 50 simulation runs with $\mu = 0.122, \sigma = 0.03$

From the demand projections, the Expected Net Present Value (ENPV) is obtained from

$$ENPV = \sum_{l}^{L} p_l \left\{ -C^0(x) + \sum_{t=1}^{T} \left(\frac{1}{1+\lambda} \right)^t (R_l^t - C_l^t) \right\} \tag{6.13}$$

where p_l is the probability associated with scenario l and L is the total number of simulations ran. For each simulation, the maximum values generated with the optimal technology selections for each exchange area is taken to calculate the maximum ENPV. This is first ran for simulations from 500 runs to 15000 runs to test for convergence. The simulations for the work moving forward are conducted using 2000 simulated paths since it gives a percentage error <0.5% and the computational cost-benefit does not seem significant for further number of runs. From these simulations maximum ENPV using optimal technologies in each exchange, is taken to be £2.42e10. The optimal technologies for the 2000 runs are found to be G.Fast and FTTP as shown in Figure 6.26. This is similar to the results found in the benchmark case.

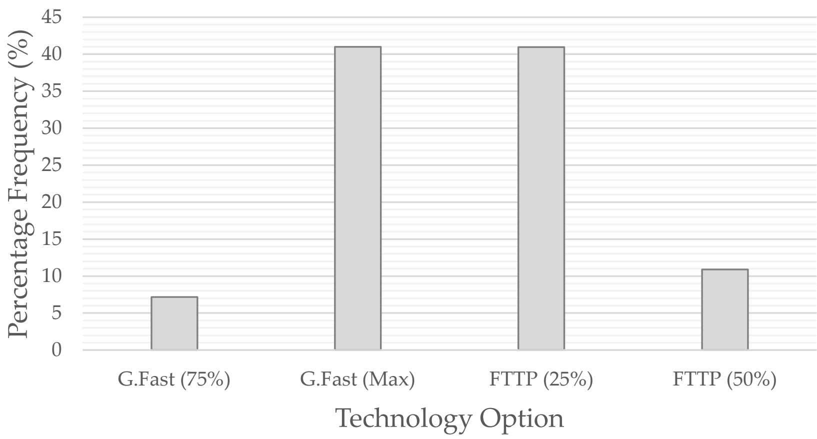


Figure 6.26. Optimal technology distributions over 2000 simulations

The optimal technologies for each individual area are represented in Figure 6.27 where the plot on the left-hand side shows the areas and the technology choice distribution and on the right, the areas that have distances greater than 4km are highlighted. This is highlighted to show that, in a number of areas which have distances greater than 4km, G.Fast is the optimal technology as shown by the corresponding bars.

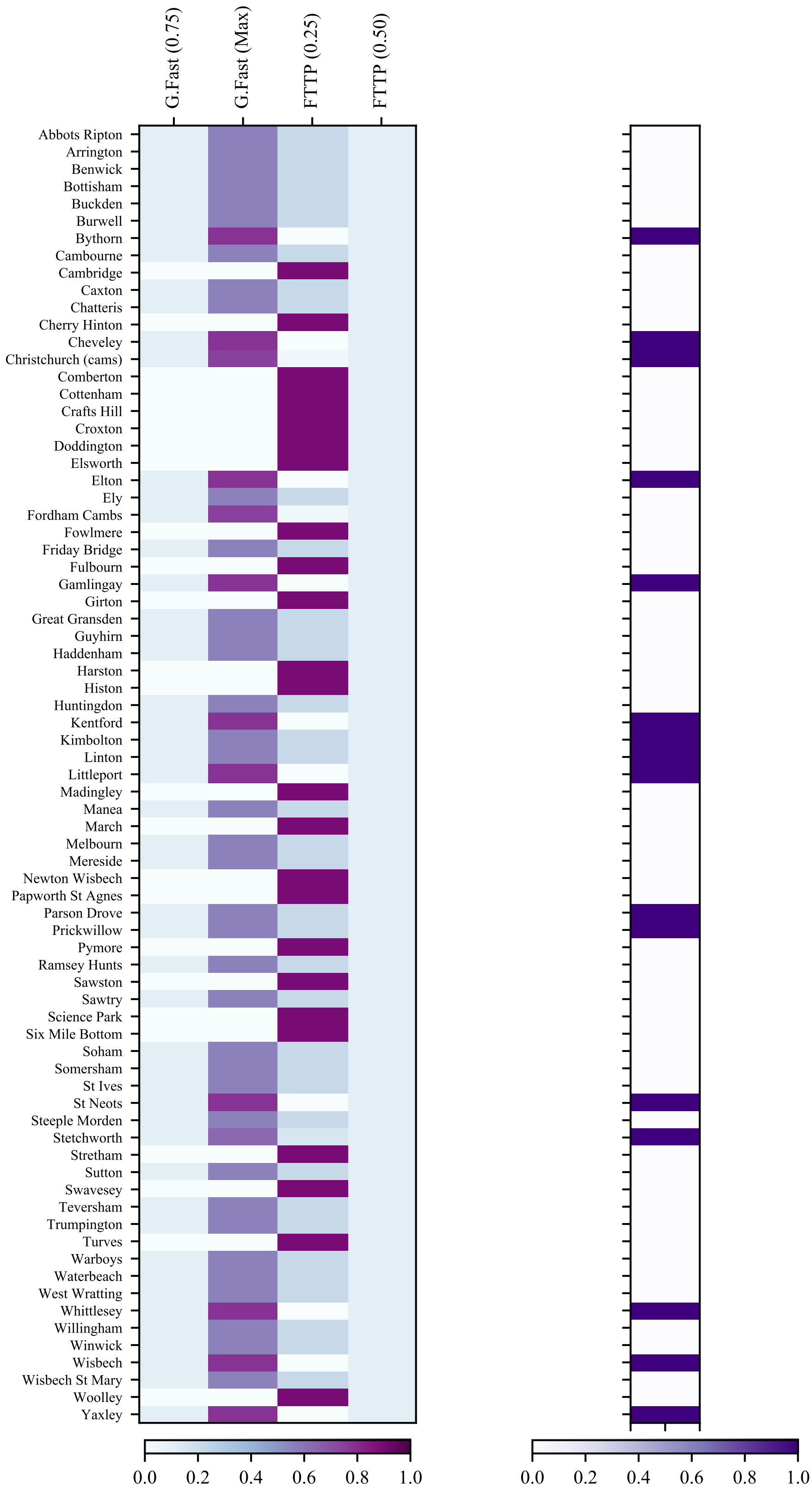


Figure 6.27. Optimal technology distributions for each area in Cambridgeshire over 2000 simulations

6.2.4 Implementation of Flexibility with Bayesian Networks

The previous results were obtained with each exchange having the same technology throughout the simulated 15-year horizon. Bayesian Networks are now introduced to this model so that technology options can be switched depending on the observed uncertainties and thus incorporating flexibility into the model. The Bayesian Network was extracted and refined from expert insight through a series of three workshops with BT. A more detailed account of model development particulars, including technical implementation, can be found in Chapter 5. Building on the Bayesian Network developed for the Waste-to-Energy system, the decision rules are shown in Figure 6.28.

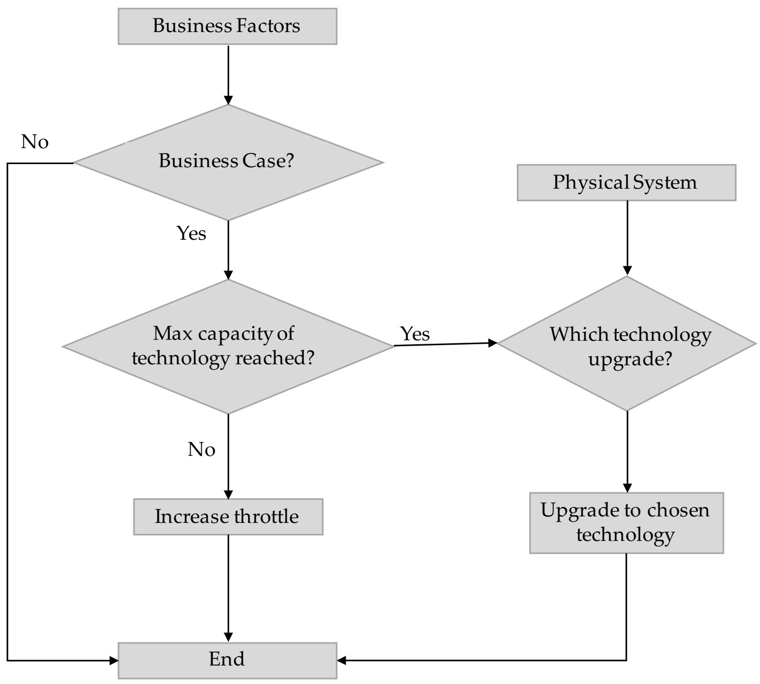


Figure 6.28. Decision rules for upgrade process

In comparison to the Bayesian Network developed for the WTE system, a larger number of business factors are incorporated such as whether the Service Level Agreement is met, the types of users expected in the area and expectation of customers. These factors are aggregated into a "Business Case" node to determine whether there is the business case for upgrading the technology. If there is a business case, the technology can either upgrade by increasing the throttle or by switching to another technology option and is based on whether the maximum capacity of the technology has been reached through throttling. The final Bayesian Network consists of 28 nodes with 51 connections and is organised to reflect the business and physical groupings as drawn in Netica in Figure 6.29. Each node, shown by a box, represents a variable and the black bars represent the probability of each state given some observation. The descriptions of the nodes are presented in Table 6.9 and dependencies, shown by the arrows between the nodes, are given in the DSM in Chapter 5.

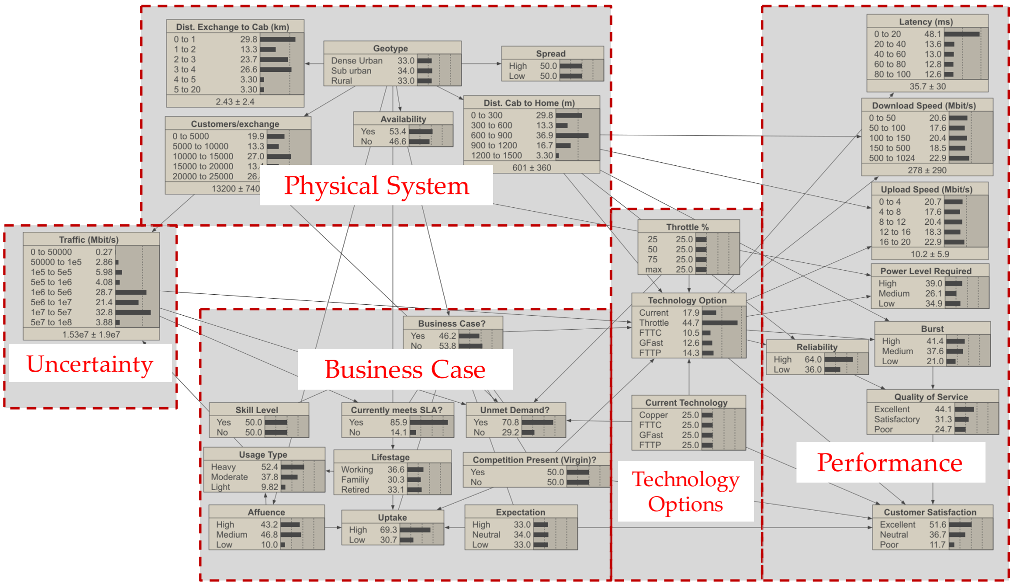
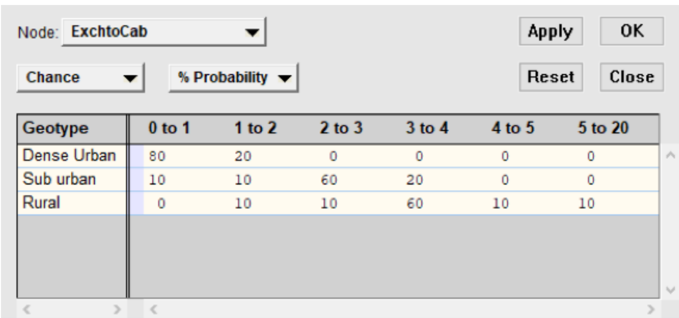


Figure 6.29. Final Bayesian Network with groupings of variables

Encoded in each node lies a conditional probability table (CPT) which allows for inference between the nodes. For example, Figure 6.30 shows a CPT from the Netica software for the Geotype node which is connected to the node representing distance from the exchange to the cabinet.



Geotype	0 to 1	1 to 2	2 to 3	3 to 4	4 to 5	5 to 20
Dense Urban	80	20	0	0	0	0
Sub urban	10	10	60	20	0	0
Rural	0	10	10	60	10	10

Figure 6.30. Conditional Probability Table for node distance from exchange to cabinet

In this case, the probability of the distance from exchange to cabinet being 0 to 1km, given that the Geotype is "Dense Urban" is 80%. Similarly, the probability of the distance being 3 to 4 km given that the Geotype is "Rural" is

Table 6.9. Node descriptions for final network

Node Name	Description
Traffic	Amount of data going through exchange. Demand from geometric Brownian motion simulations.
Dist. Exchange to Cab (km)	Distance from the exchange to cabinet.
Customers/Exchange	Number of customers per exchange.
Geotype	The type of area characterisation.
Availability	Whether the technology upgrades are available in the area.
Spread	Whether the spread of houses in the area is uniform or clustered.
Dist. Cab to Home (m)	Distance from cabinet to home.
Business Case?	Whether there is a business case.
Skill Level	Whether engineers in the area have sufficient skills to install new technology.
Currently meets SLA?	Whether the area is currently meeting Service Level Agreements.
Unmet Demand?	Whether the demand/traffic is great than that installed.
Usage Type	Whether the customers use data heavily (i.e streaming TV).
Lifestage	The type of residents in the premise.
Competition Present (Virgin)?	Whether there is competing companies in the area.
Affluence	The wealth of the area.
Uptake	Whether customers may opt for the technology once installed.
Expectation	The customers' belief in the technology.
Throttle %	The amount of throttle applied.
Technology Option	The technology to be installed in that year, if any.
Current Technology	The technology that is currently installed that year.
Latency (ms)	The delay of data transfer.
Download Speeds (Mbit/s)	The speed at which data can be transferred from internet to computer.
Upload Speed (Mbit/s)	The speed at which data can be transferred from computer to internet.
Power Level Required	How much electricity is required.
Burst	Whether there are spikes in demand.
Quality of Service	Performance measure of the network.
Reliability	Whether the data is transferred successfully.
Customer Satisfaction	Whether the customers are satisfied with the service.

60%. Using various inference methods probabilities of the other nodes can be inferred given some observations. When running the simulation, the observations represent the state of the exchange observed at that time slice and the technology currently deployed. The maximum value of the probabilities in the “Technology Option” node then represents the technology option that the exchange should upgrade to in the next time slice, if any. If there are no upgrades necessary, the “Current” option will be the maximum value in the “Technology Option” node and if the throttle is to be increased, the “Throttle” state will become the maximum value. Figure 6.31 shows an example where observations, as indicated by the grey nodes, are given in the traffic, distance cab to home, throttle % and current technology nodes. The Bayesian Network then gave the recommendation to upgrade to FTTP.

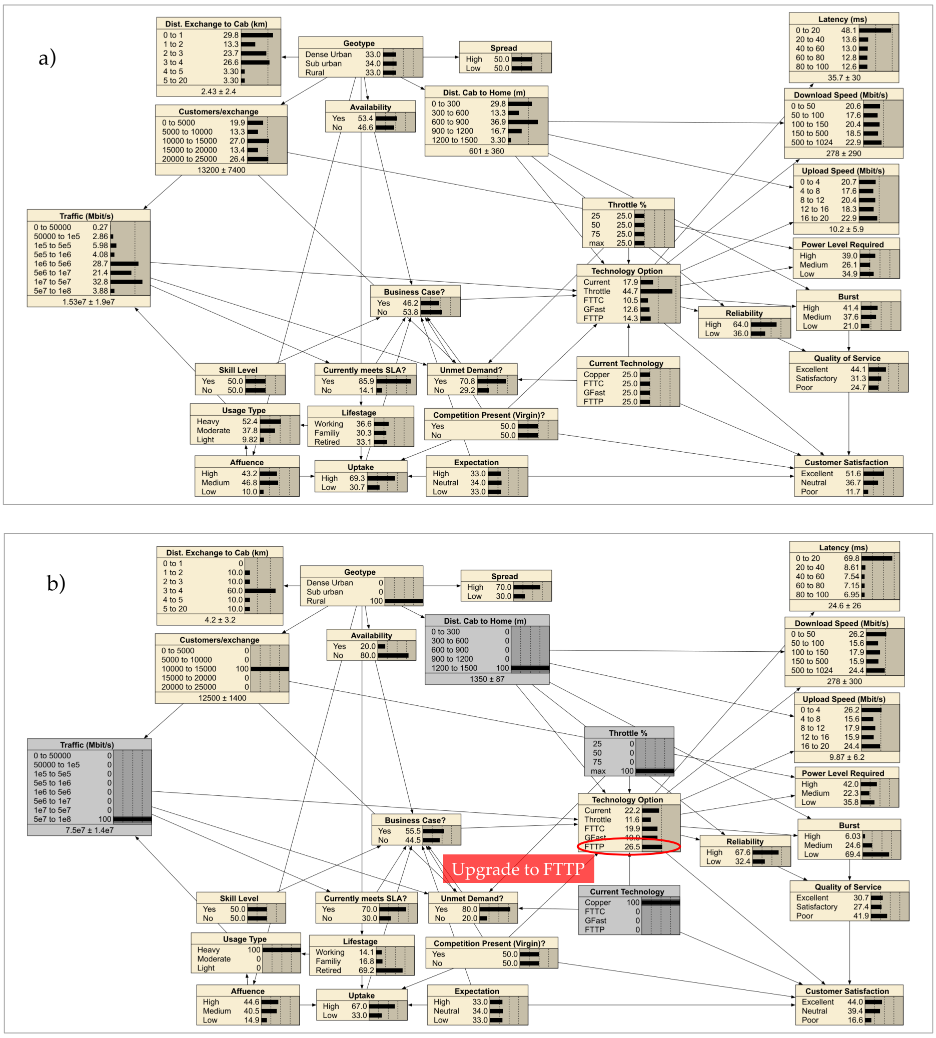


Figure 6.31. Bayesian Network with (a) no observations (b) observations indicated in grey

The network was then coded into Python using the *pomegranate* package for probabilistic modelling so that experiments could be ran in batches. Observations and results were also compared to the Netica software to validate the behaviour of the network. Since the node of interest is the "Technology Option", observations are input to the parent nodes: "Traffic", "Distance Cabinet to Home", "Throttle %" and "Current Technology". These said nodes thus are assumed to account for evidence of connecting nodes up the chain. The recommendation of every combination of observations for these four nodes are calculated to check the classification behaviour of the network. Each bar in Figure 6.32 shows the percentage frequency that the respective technology is recommended over the 640 combinations of observations.

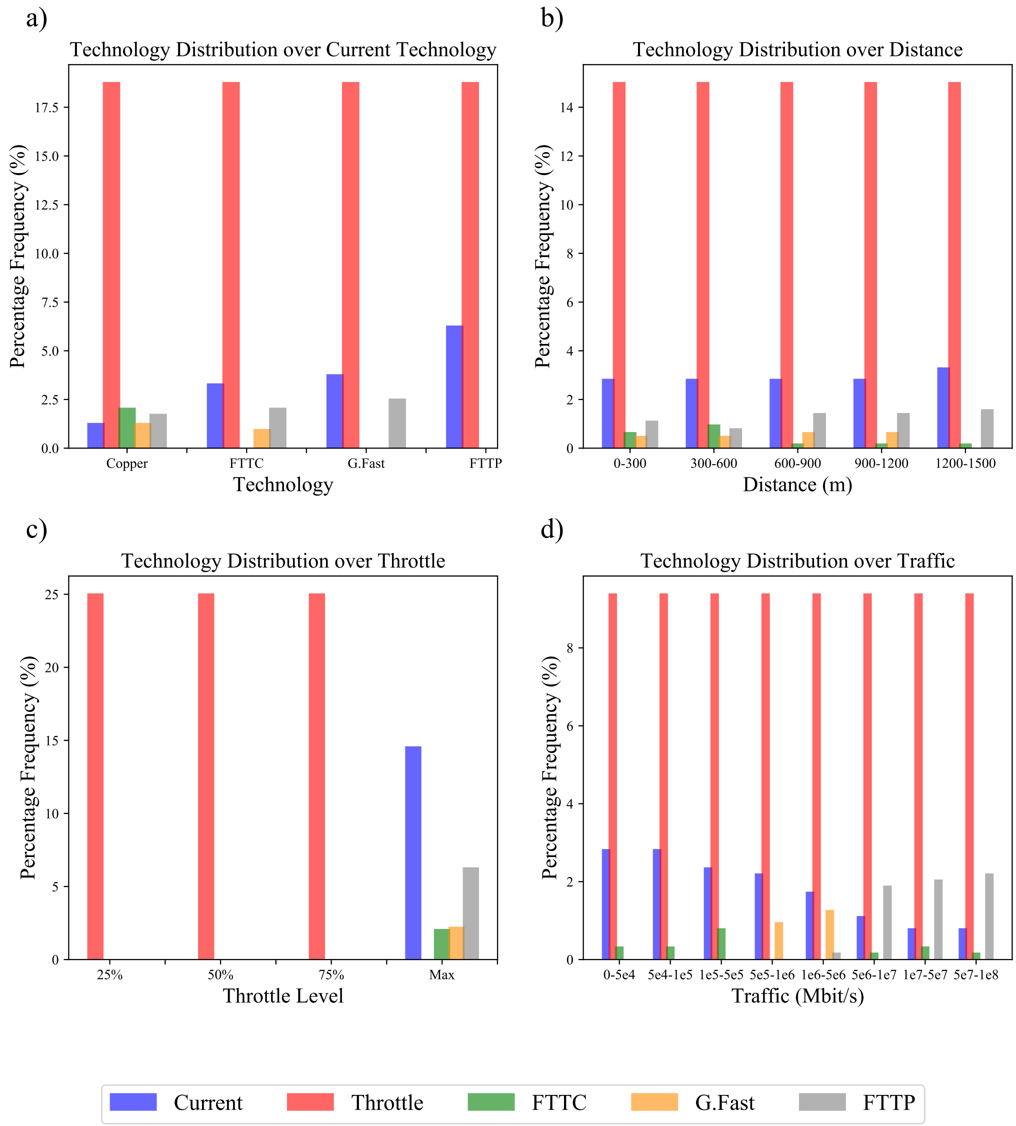


Figure 6.32. Verification of Bayesian Network behaviour

In Figure 6.32.a, the first set of bars illustrate that when the exchange currently has copper technology, it can upgrade to any of the technologies as shown by the presence of all bars. Similarly for when the current technology is FTTC, it can upgrade to any apart from itself as shown by the missing green bar. For G.Fast, it only recommends upgrades to FTTP (gray), throttle (red) or keep the current technology (blue) and for FTTP, the exchange can only either increase in throttle or keep the current technology. For the recommended technology upgrade distribution with distance in Figure 6.32.b, there is a tendency to switch to FTTP with increasing distance. In Figure 6.32.c, the Bayesian Network recommends, as designed, to throttle until the maximum capacity is reached upon which it recommends to switch or keep the current technology. Finally, Figure 6.32.d shows recommendations in favour of FTTP with increasing traffic, G.Fast for medium traffic and FTTC where there is less traffic. In general, these trends are as designed to model expert assumptions from meetings within BT.

6.2.5 Design Space Exploration

The fourth step in this framework is to find the optimal technologies for each area. The model is ran with 2000 simulations as previous, starting with Copper technology, throttled at 25% and the most common classifications resulting from the Bayesian Network for each area over time is shown in Figure 6.33. The most common classification is shown, as opposed to the classifications that give the highest ENPV, since the latter would bias towards technologies which give the highest capacities. It can be seen that in the early years, the Bayesian Network recommends upgrading of the network through throttling and a number of areas are upgraded to FTTC. At around $t = 7$, this switches to recommendations for keeping the current technology as shown by the majority of blue patches. The current technologies at each time slice in each area over time is shown in Figure 6.34. It shows the upgrade process for each patch starting with Copper technology, throttled at 25%. The majority of areas upgrade to FTTC over time as per the Bayesian Network classifications and some to G.Fast as shown by the green and orange colouring. Only the Cambridge area upgrades to FTTP at $t = 15$. This is as expected due to the larger population in the Cambridge area and contrasts to the earlier results where the optimal fixed technologies were G.Fast and FTTP for the majority of other areas.

These figures demonstrate the Bayesian Network switching technology over time. Furthermore, the increased value of upgrading, or the Value of Flexibility, can be determined by comparing the simulations with no upgrades as calculated

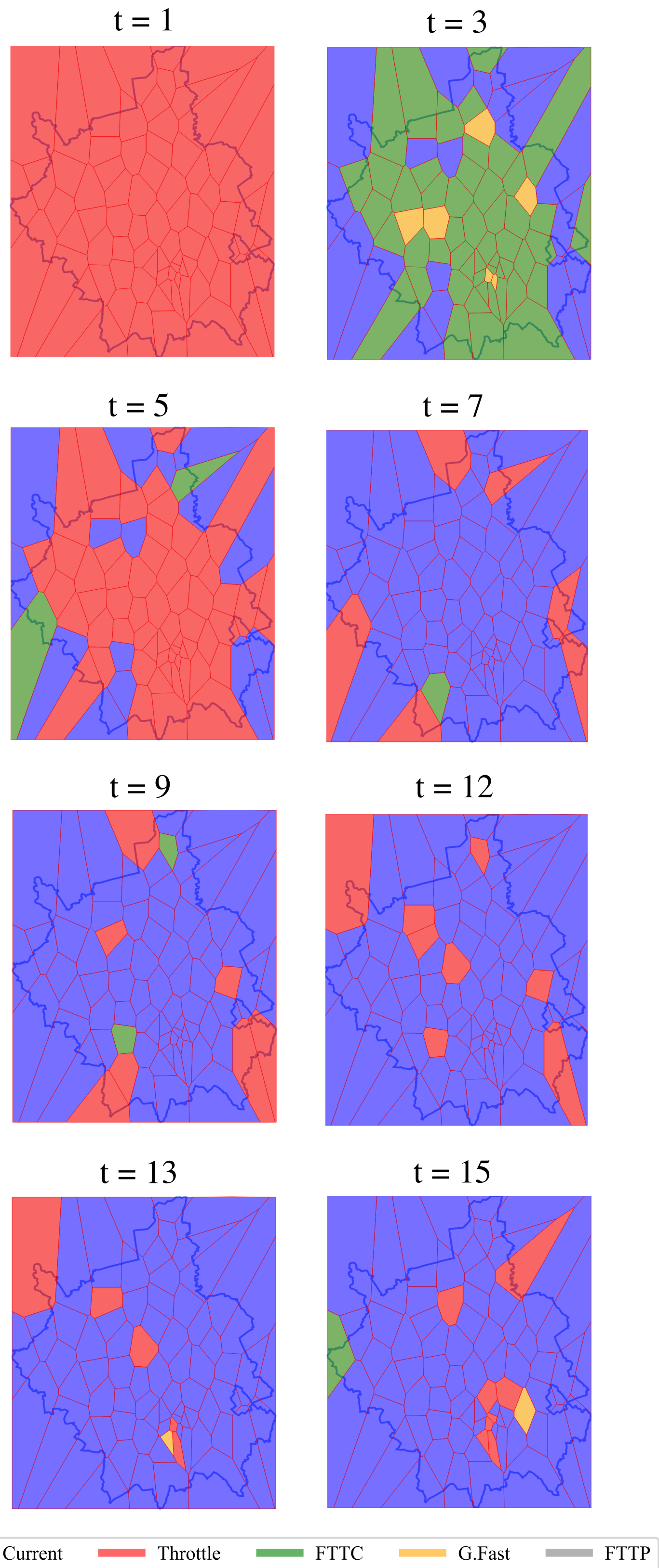


Figure 6.33. Bayesian Network classification at each time slice, initialised with copper technology

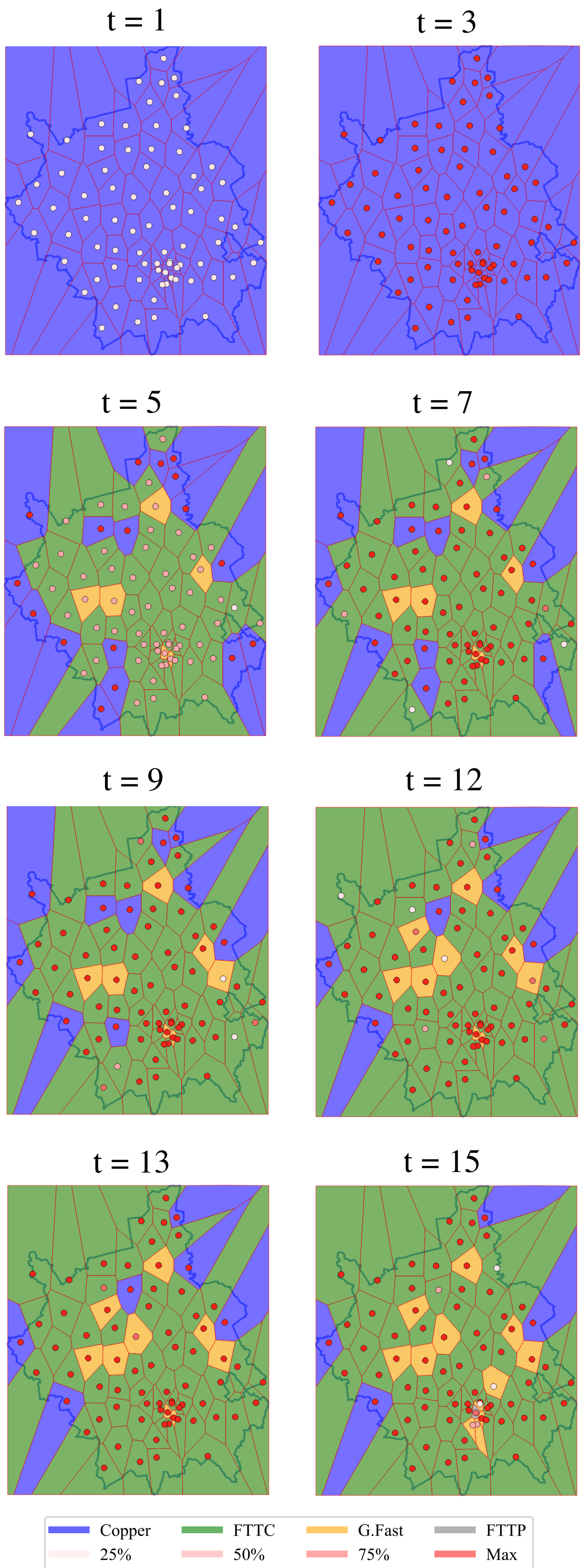


Figure 6.34. Installed technology at each time slice, initialised with copper technology

from step 2 (Uncertainty Recognition) and the results from this step where there are upgrades. A full table with absolute values are given in Table 6.10 for comparison of values. The table shows how there is marked increase in ENPV with greater capacities as expected, shown by increasing values moving down and across the table. However, these improvements only occur up to around an initial technology of G.Fast at maximum capacity, after which the ENPV plateaus with more upgrades. This is due to the demand in the simulations peaking within the maximum capacity of G.Fast and thus further upgrades or starting at high capacity does not generate further revenue.

Table 6.10. Absolute ENPV values for upgrades against initial capacity

Initial Technology	Throttle	Capacity (Mbits/s)	Total ENPV (£ million)					
			Upgrades = 0	Upgrades = 2	Upgrades = 4	Upgrades = 6	Upgrades = 8	Upgrades = 10
Copper	25%	6	76	1,230	2,147	8,601	10,685	11,189
	50%	12	606	2,346	6,050	11,795	11,867	12,362
	75%	18	1,487	2,718	9,504	11,909	13,086	13,303
	Max	24	2,722	6,632	13,633	13,676	14,396	14,396
FTTC	25%	19	214	8,450	11,488	15,782	16,538	16,681
	50%	38	3,991	15,452	15,208	17,615	17,808	17,808
	75%	57	10,284	13,335	17,630	18,386	18,528	18,528
	Max	76	16,183	15,917	18,324	18,517	18,517	18,517
G.Fast	25%	82.5	9,016	20,602	22,168	22,560	22,560	22,560
	50%	165	16,294	22,366	22,560	22,560	22,560	22,560
	75%	247.5	20,602	22,168	22,560	22,560	22,560	22,560
	Max	330	22,366	22,560	22,560	22,560	22,560	22,560
FTTP	25%	256	22,122	23,474	23,474	23,474	23,474	23,474
	50%	512	23,474	23,474	23,474	23,474	23,474	23,474
	75%	768	23,474	23,474	23,474	23,474	23,474	23,474
	Max	1024	23,474	23,474	23,474	23,474	23,474	23,474

This is further visualised in Figure 6.35 where the Value of Flexibility, obtained by subtracting the ENPV of the robust model (0 upgrades) with the flexible case (multiple upgrades), is plotted. The blue area shows where there is not much value added and clearly, as discussed, initial technologies greater than 11 (G.Fast) do not gain significantly from upgrading since the capacity is already suffice. The greatest benefit lies in upgrading if the starting technology capacity is low, such as with Copper, and less benefit if the starting technology capacity is near the optimum such as with G.Fast. Furthermore, there are two ridges, one with the initial technology around 4 (FTTC at 25%) and another at where the initial technology is 8 (G.Fast at 25%). The first peak occurs since FTTC, with a few throttle upgrades it can tap into a substantially higher capacity which better captures demand even without upgrading to another technology. A second peak is found since the relative initial cost of G.Fast is high compared to FTTC, giving a low ENPV for the robust solution. However, through throttling which is relatively inexpensive, a much larger capacity can also be utilised to achieve a high ENPV. In these results, it should be noted that the initial capacity is plotted against the maximum number of upgrades and therefore the Bayesian Network does not necessarily upgrade 10 times.

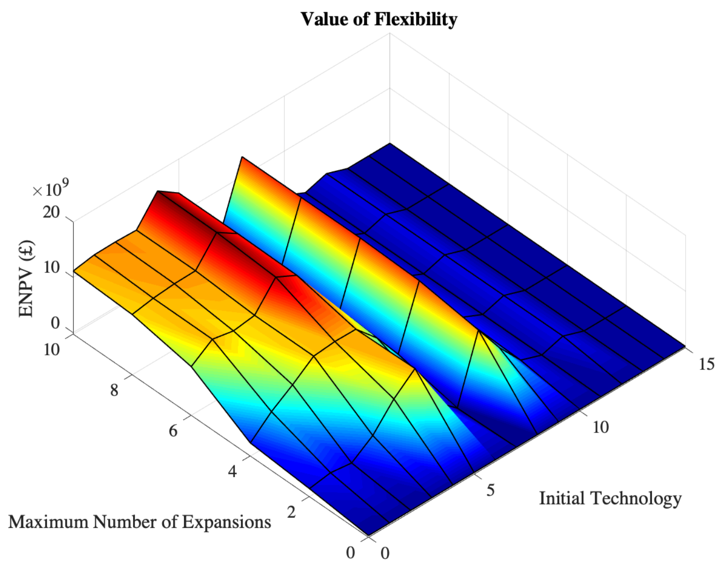


Figure 6.35. Visualisation of the Value of Flexibility

The order of these upgrades can be visualised in Figure 6.36 and shows that Bayesian Network may recommend to jump between technologies. These upgrade paths as shown are with the network initialised to copper, FTTC, G.Fast and FTTP. The 16 technology options shown on the axis represents enumerations of the 4 technology options and the 25% increments in capacity. Copper (blue circles) seems to upgrade in 3 main windows: at year 3 some simulations upgrade straight to FTTC as shown by the jump to Technology Option 8; between year 3 and 10 there seem to be multiple instances of throttling; and after year 13 there is further throttling. FTTC exhibits 2 upgrading windows: the first at year 3 continues to upgrade via throttle and the second at around year 8 marks the next window of upgrading through throttle. G.Fast also seem to upgrade in 2 windows: the first in year 4 and 5 where the throttle is increased and in year 11, 13 and 14 where the throttle is increased. FTTP is also seen to throttle until it reaches maximum capacity.

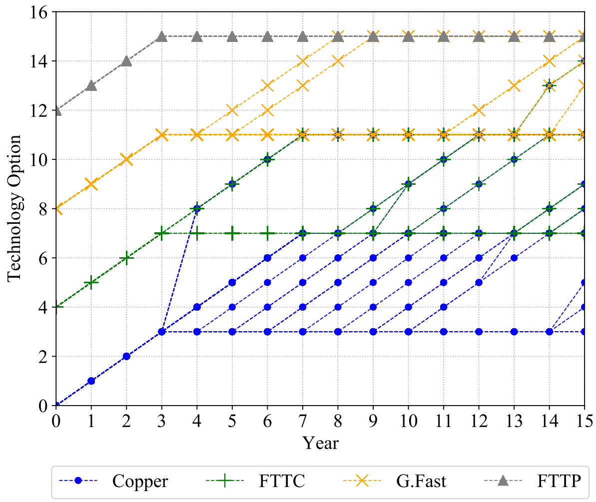


Figure 6.36. Upgrade paths for each technology

6.2.6 Resilience Analysis

The final step of this framework is to examine the response of the system to changing uncertainties and explored through changing volatilities and drift in this study. The results of the final technologies in each area at $t = 15$, initialised with copper at 25%, with varying drift is shown in Figure 6.37.

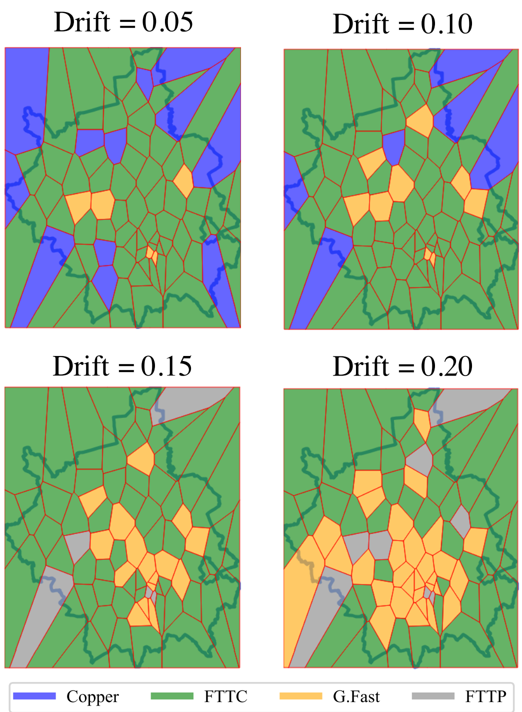


Figure 6.37. End technologies at $t = 15$ in each area with varying drift

As the drift or growth of demand is increased, so is the tendency to move towards FTTP, the higher capacity line, as shown by the increased number of gray areas. G.Fast also appears to be more abundant with increased demand due to being a higher capacity technology. The effect of volatility on the technologies at $t = 15$ were not significant and thus not shown.

The upgrade process can be visualised and Figure 6.38 shows the impact of varying volatility with copper as the starting technology for Cambridgeshire and keeping drift to 0.1. Each path is given transparency by setting the alpha of the plot, such that the darker or more solid circles represents states which occur more often. It is seen that with increased volatility, there are skips in technology as represented by the increased gradient of the paths. Furthermore, it can be seen that there are fewer paths in the higher volatility cases with jumps straight to the higher capacity technologies in the early years. This is due to the high volatility triggering the Bayesian Network to expand to high capacity and thus to capture more demand. At lower volatilities, there are smoother transitions with more upgrades in throttle as shown by the evenly spread dots in volatility= 0.01. As noted before, the end technologies at $t = 15$, however, remain the same despite the different upgrade process.

Another study, keeping the volatility constant at 0.01 and varying drift, is shown in Figure 6.39. It shows that with increasing drift, higher capacity technologies are used and is shown by the paths shifting into the top right of the graphs. With drift=0.2, by year 12 there are no simulations that remain with copper technology. This is expected with the increased demand from increasing drift. Furthermore, with low drift, it seems that the paths become less uniformly spread and there are jumps in technology. Where the drift is higher, the lines are mostly parallel to each other.

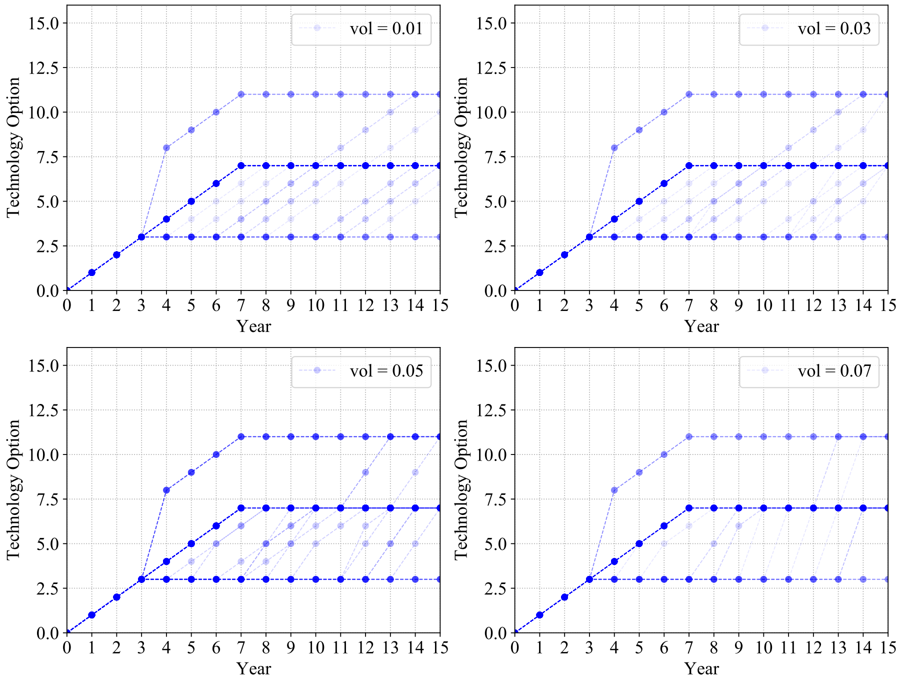


Figure 6.38. Upgrade paths of copper technology with varying volatility

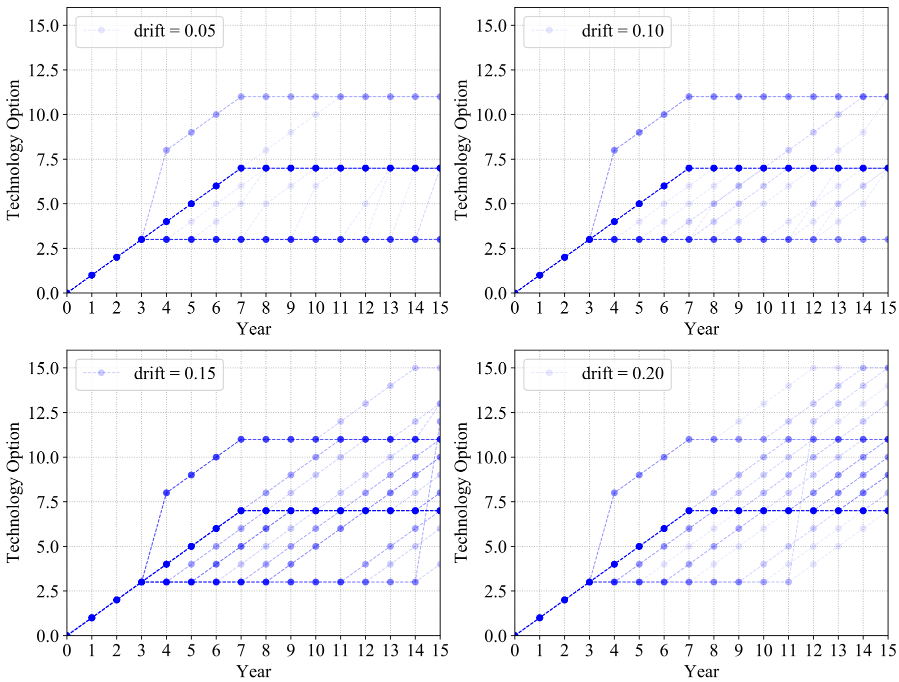


Figure 6.39. Upgrade paths of copper technology with varying drift

The research questions and business requirements pertaining to what and when to invest in particular technologies have been addressed in the previous results. Now, the trade-offs between the robust and flexible strategies may be explored. Using the initial capacity as a proxy for robustness and the maximum number of upgrades for flexibility, the surface of ENPV for drift = 0.122 and volatility = 0.03 as per the original demand projection is shown in Figure 6.40 with the top view shown in Figure 6.41.

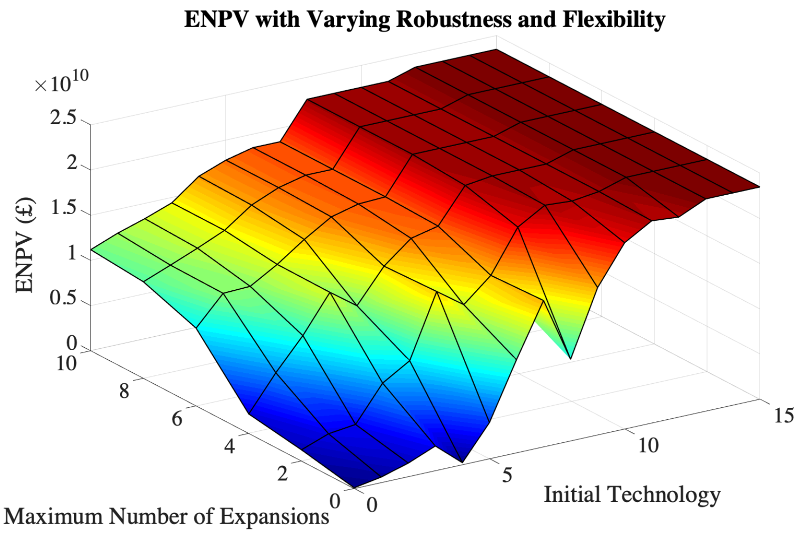


Figure 6.40. ENPV surface for BT case against maximum number of upgrades and initial capacity

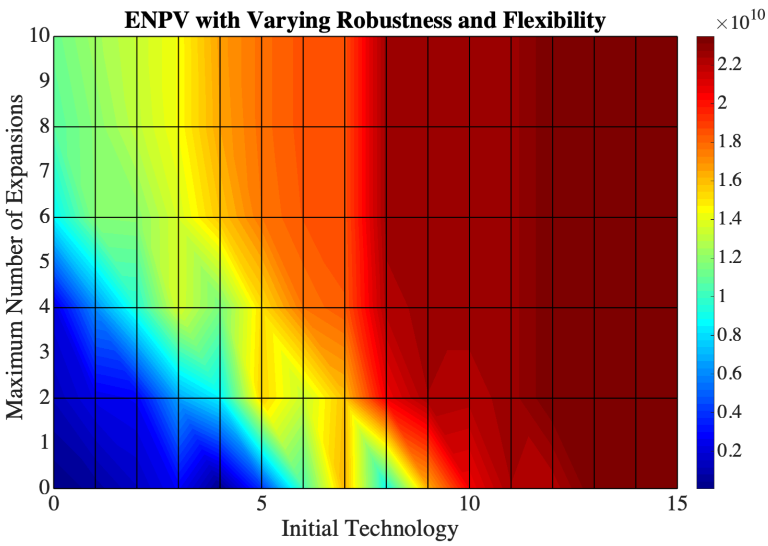


Figure 6.41. Top view of ENPV surface for BT case against maximum number of upgrades and initial capacity

These plots are similar to those found in the Waste-to-Energy system, giving further confidence in the model. Comparing to the results from that case study, it can be identified that due to the relatively high drift, there is a high ENPV where there are high capacities. This can also be achieved through either a high initial capacity or a lower initial technology with more upgrades. The total combination of initial capacity and upgrades have to serve some amount of demand which results in the diagonal trade-off slope. As the total combined capacity increases, the ENPV also increases due to the ability to convert more demand into revenue. The ENPV plateaus toward the top of Figure 6.41 where there are many upgrades which indicates that, although the Bayesian Network can, there is not the need to upgrade. This surface generally fits the results from the first case study but without the drop in ENPV on the right of the diagram. In the first case study, this was due to the demand not meeting the capacity of the system and thus there was a deficit. For this case, the demand is sufficient to offset installation costs. That said, theoretically there should be a similar drop if there were other technologies available at higher capacity and insufficient demand.

The effect of varying volatility and drift on this surface is now examined and are shown in Figure 6.42 and Figure 6.43 in the following pages respectively. First, volatility is varied with drift of the demand kept to 0.1. Similar behaviours are shown as per the first case study and it is seen that varying the volatility does not seem to change the characteristics of the surface. There is a slight shift of ENPV towards higher capacity technologies which give higher ENPV due to more of the demand being captured. The response to varying drift and keeping volatility to 0.03, however, is more dramatic as shown in Figure 6.43. The original demand projections used a drift of 0.122 and volatility of 0.03 so reference can be made to the second set of plots. It can be seen that there is generally an increase in ENPV with increasing drift or growth of demand as expected. The slope towards the higher capacities increase more due to the ability to capture more demand and there is a dramatic jump in the last set of results with a sharp increase in ENPV. This is due to the growth in demand triggering FTTP, the highest capacity technology earlier, so that all of the demand can be converted to revenue. Furthermore, once the Bayesian Network recommends the switch to G.Fast, it is unlikely to switch again to FTTP unless there is significant increase in demand and so it becomes limited in capacity.

Looking at the trade-off between flexibility and robustness, the Waste-to-Energy system suggested that for the original configuration of the system, flexibility would always give better ENPV. Here, this seems to not be the

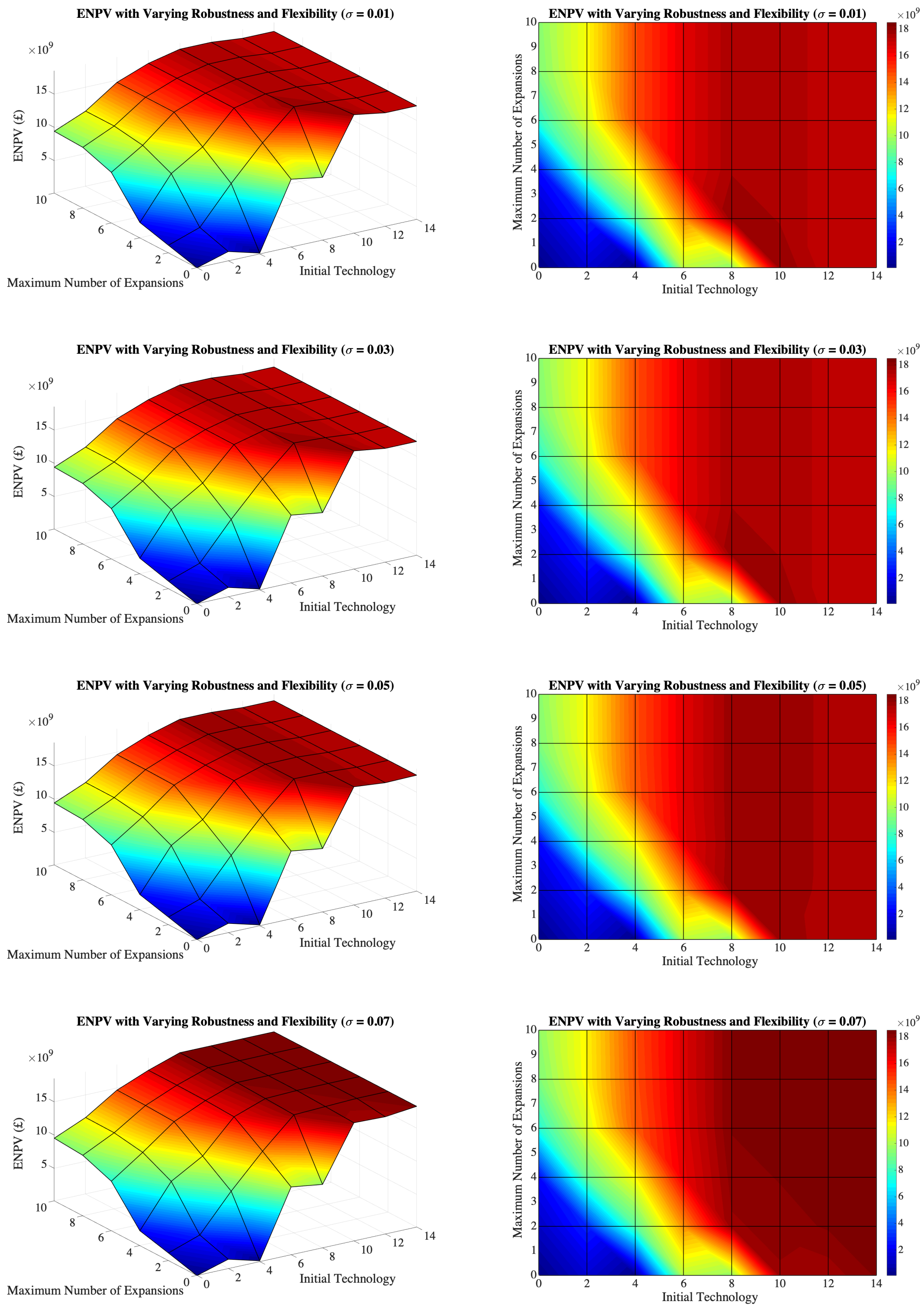


Figure 6.42. ENPV surface with initial capacity, maximum number of expansions and varying volatility

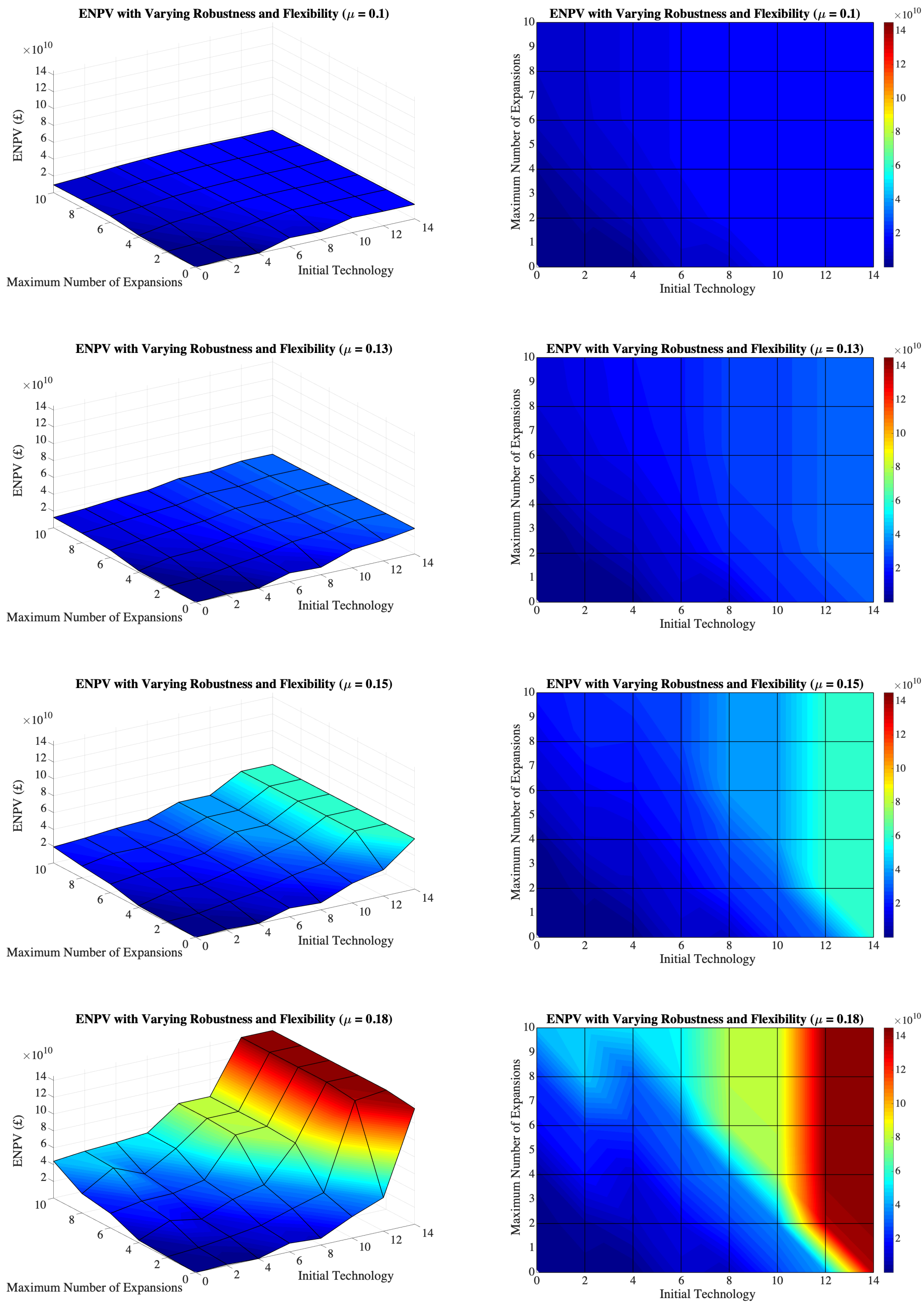


Figure 6.43. ENPV surface with initial capacity, maximum number of expansions and varying drift

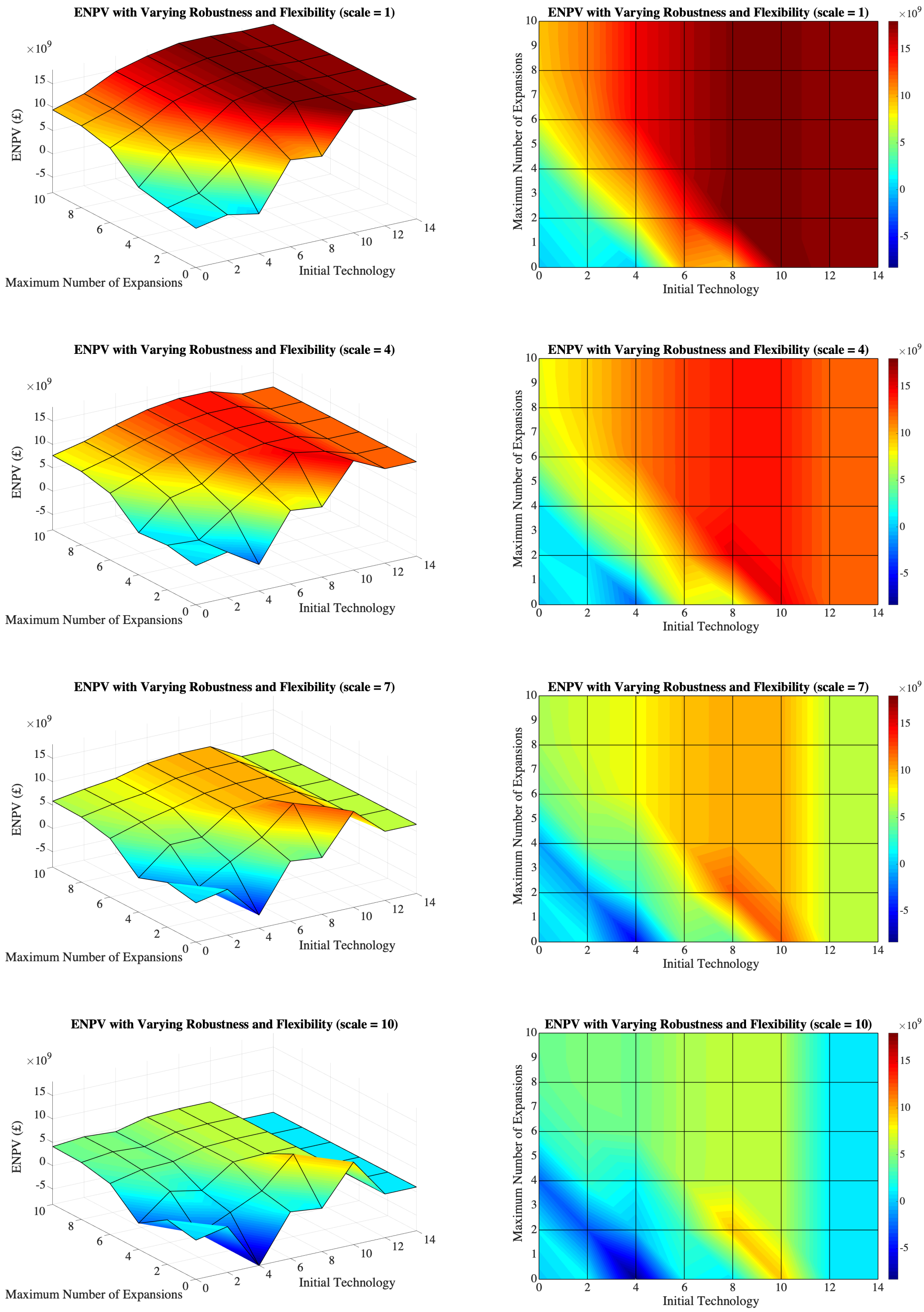
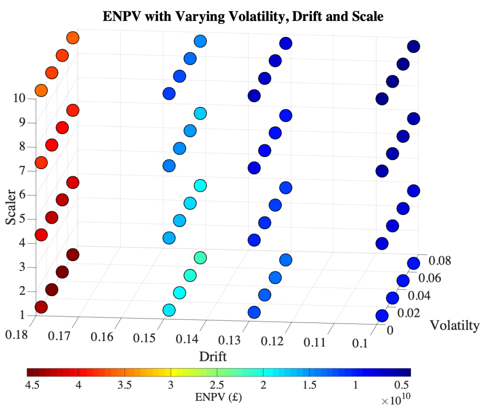


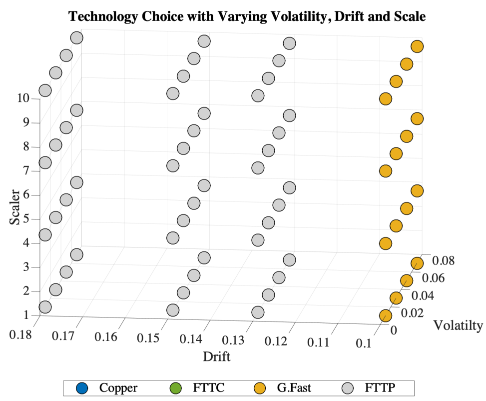
Figure 6.44. ENPV surface with initial capacity, maximum number of expansions and varying expansion cost

case looking at the plots. Indeed, looking at the absolute values in Table 6.10, the ENPVs plateaus at FTTP showing that there is no increase in revenue with further upgrades. This is due to the Bayesian Network not actually making any upgrades despite having the ability to increase further. While a case could be made to plot against the actual number of upgrades, this would have required the manipulations of the conditional probability tables to adjust how likely the Bayesian Network recommends upgrades and some consistent way of making the expansions a specific number. The changes in surface shape, however, are similar with increasing expansion costs. Here, a scalar is multiplied by the upgrade costs for each technology and the corresponding surface with drift = 0.1 and volatility = 0.03 is shown in Figure 6.44 with the top view on the side. Similar to the Waste-to-Energy Case, as the expansion costs, or the scalar multiplier, is increased, it suggests that a robust design may be better. That is not to say the ENPV increases, but where there are high expansion costs, it is better to have no upgrades and the whole surface decreases in ENPV. A small ridge forms where the initial technology option is G.Fast at 75% (option 10) and is consistent with previous results where G.Fast is shown to be profitable.

Finally, a scatter plot of the technologies under these different parameters can be plotted. Figure 6.45 shows the maximum capacity technology used in the whole of Cambridgeshire over the simulations and the corresponding ENPV. Similar to discussions before, the higher capacity technologies are favoured with increased drift, there is reduced ENPV with increasing expansion costs and volatility seems to have little effect on the chosen technology and ENPV.



(a) ENPV with drift, volatility and expansion cost



(b) Optimal technologies with drift, volatility and expansion costs

Figure 6.45. Combined effects of drift, volatility and expansion costs on ENPV and optimal technologies

6.2.7 Discussion & Summary

The support method developed through this work has been applied to a telecommunications case with BT and significant contributions include working with industry experts to build the Bayesian Network as well as using the model to select technology options. This was completed for Cambridgeshire where the task was to understand what and when to upgrade technologies having the choice of Copper, FTTC, G.Fast and FTTP.

First step in the framework was to gather data to build an initial robust model where there were no upgrades available and to calculate the resulting NPVs. It should be noted that revenues and costs are based on Openreach catalogues and the values in general are for proof-of concept only. The actual upgrade process and thus costs are much more complex than considered here. Indeed, the calculated ENPVs are inflated but do show the overall characteristics that were expected. Furthermore, it suggested that there could be some correlation between the distance and type of technology deployed but this is not further pursued due to inaccurate data. Uncertainty was added in the form of demand based on historic data, albeit the projection was lowered due to there being no available technologies currently which could accommodate the projections using historic data. Using original projections the model would have recommended all areas to be upgraded to FTTP due to the significant growth in demand and perhaps the better strategy would be to research new technologies as opposed to choosing between existing options. It was also assumed that revenue was a function of demand but in reality this is not strictly the case and it was mentioned by one of the experts that the first 10Mbit/s is the most valuable to customers. Industry experts have suggested that there are diminishing returns as the demand is increased and not all customers would need to continually upgrade. That said, both the NPV calculations and the geometric Brownian motion technique used to simulate demand are well established processes and easily modified for further use.

One of the main contributions of this work involved implementing flexibility with Bayesian Networks. This was tested with industry experts and it was generally well received. When presented to industry stakeholders, the Bayesian Network offered a white box approach that machine learning techniques are often criticised for and gave an intuitive method of visualising the system. In addition, factors from both the business side and physical attributes of the system could be considered making this a powerful technique. While the construction of Bayesian Networks in terms of structuring and conditional probability tables could leverage expert domain knowledge, this also leaves it open to biases and remain an active area of research. That said, the author was able to manipulate the Bayesian Network to give particular behaviours for decision making and found it a useful approach for working with industry. With the model built, the recommendations for each area from the Bayesian Network could be examined to understand the upgrade process.

The final contribution of this work was to assess how the system responds to uncertainty and the volatility as well as drift were varied to examine their effects. Volatility did not seem to affect the end technologies at 15 years but did change the upgrade process in that higher capacity technologies were selected earlier. The drift or growth rate of demand was the major influence in the ENPV values and was as expected since the revenue was modelled from demand. The trade-off surfaces compared similarly to the Waste-to-Energy system and upon initial exploration of the solution space, the characteristics of the BT case could be mapped to findings in the previous case. Similarly, as the drift increased, so did the need for more upgrades and increased initial capacity, whereas while the volatility increased, there was a tendency to jump straight to high capacity technologies. This is expected since the high volatility would have triggered the decision rules. Due to the high growth rate of demand, there is definitely the need to upgrade and employ the flexible strategy especially if the area is still with copper technology. It may even be suggested that if the demand projection is similar to the historical data with high growth rate, another technology not currently available will be needed by 2032. That said, there would also need similar growth in the technologies that require such high bandwidth, such as virtual reality, to use this capacity.

Coming back to the design strategies, there is the clear need for flexibility, especially if the current area is at Copper, in this case due to the high growth in demand. There is a diagonal trade-off slope that appears in the surfaces which enable decision makers to understand the number of upgrades that would be necessary for a given initial capacity to maintain a similar ENPV. Succinctly, if the higher capacity technologies are installed such as G.Fast or FTTP, then a robust solution is suffice and no more upgrades are required. On the other hand, if there are lower capacity technologies installed then the diagonal slope can be used to understand this trade-off.

Chapter 7

Discussion

The previous chapter applied the support method developed through this work to two case studies and presented the results of resilience analysis. Attention now turns to an evaluation of the support method and discussion of whether resilience has duly been assessed for engineering infrastructure systems. In particular, from principles in engineering design, the focus and contribution of this work has been to build both understanding as well as synthesise a model to analyse resilience in engineering infrastructure systems. As such, each subsection in this Chapter answers the Research Questions posed in Chapter 1 and emphasises the need for new knowledge and modelling capabilities. First conceptual insights and design strategies for resilience in engineering infrastructure systems are discussed. This is followed by reflections of the technical implementation and application of this newly developed support method. Finally, the success, impact as well as limitations of this work are given, prompting areas for further investigation.

7.1 On Understanding Resilience

The first contribution of this work pertains to an improved understanding of the concept of resilience and the design strategies that enable resilience in engineering infrastructure systems. This was important due to the wide applicability of resilience and it was necessary to first understand how to contextualise the many facets of resilience for this work. As such, the first set of research questions aimed to improve the understanding of resilience in engineering infrastructure systems and are repeated below for convenience.

Table 7.1. Research Questions: Understanding Resilience in Engineering Infrastructure Systems

Understanding Resilience in Engineering Infrastructure Systems	
RQ1	What is a useful definition of resilience for engineering infrastructure systems?
RQ2	What engineering design properties are required by engineering infrastructure systems to enable resilience?

7.1.1 Defining Resilience

The first research question was necessary to give a working definition of resilience for the foundations of this work. Indeed, there has been many perspectives on resilience and it may have been the case that not all views from other domains also apply to engineering infrastructure systems. For example, engineering infrastructure systems are characterised by long lifecycles and large upfront costs which suggests that such systems should be designed strategically. This could further mean that the system is subject to changing requirements necessitating upgrades in future. Such a design requirement, however, is seldom found in traditional engineering resilience literature where the aim of resilience is to maintain the status quo and "absorb disturbances" through redundancy. While it is necessary so that engineering infrastructure systems are able to maintain operational constraints such as fulfilling demand, it was not sufficient in enabling a strategic view. The literature search was thus extended to the fields of management and ecology to seek alternative perspectives. In management literature, the focus was on "adapting" resources to keep business as usual and how to prevent chaos in the face of disaster. Again, this view was useful, but not sufficient for engineering infrastructure systems. The strategic view that seemed to be missing from the earlier reviews was found in ecological resilience, prompting for its inclusion in the literature review. From the perspectives of these three communities, these characteristics were amalgamated to form the definition of resilience for engineering infrastructure used in this work, given as,

Resilience Definition
Resilience is the system's response to uncertainty, be it risk or opportunity, through both robust and flexible strategies such that it continues to function to the fullest possible extent over time.

This definition, while broad, captures the necessity of resilience to encompass both the positive and the negative. That is, designing an engineering infrastructure system to be resilient should enable systems to not just endure risk but also allow the system to grow should the opportunity arise. This definition need not be specific to an engineering infrastructure system since other systems may also require such a view and this definition is deliberately left broad so that it may be applied in other contexts whilst highlighting this shift in perspective to account for a spectrum of risk and reward.

For engineering infrastructure systems, the definition is also necessarily abstract due to the wide ranging types of systems in this domain. Here, this perspective has been applied to investing in telecommunications infrastructure and Waste-to-Energy systems. Uncertainty in both cases have primarily been taken to be demand from customers and functioning to the fullest possible extent has been explored through the maximisation of the system's economic lifecycle values, measured by expected net present value (ENPV). However, infrastructure systems are often subject to a myriad of uncertainty including government pressures, competition and fluctuation in commodity prices *etc* and so, uncertainty here is loosely defined so that this definition of resilience can be applied across different systems where uncertainty may not be demand. A similar argument is held for mapping performance to ENPV. While a financial metric is convenient to map performance across a number of domains, it may be such that the target metric is not financial incentive. For example, in a telecommunications example, there may be the need to maintain uptime of servers and thus uptime as a metric may be more convenient for domain experts and engineers. This metric could, however, be mapped to finance, but whether it should depends on stakeholders involved. As such, these definitions are loose to maintain applicability of this work to other systems, but demand and ENPV have been demonstrated to be useful in this work.

What the definition does highlight and differs from other definitions is the role of the system's response – whether the system changes – through robust and flexible strategies. This is the key contribution in the understanding of resilience in engineering infrastructure systems from this work. It draws together ideas from engineering, management and ecological studies of resilience and advocates for design strategies to enable particular behaviours of the system. This nuance to the definition for resilience in engineering infrastructure systems has been useful and embodies the focus of this work.

7.1.2 Design Strategies for Resilience

The characteristics of resilience found from the literature review were mapped to the three engineering design of: robustness, adaptability and flexibility. Robustness is where a system is designed with enough redundancy so that it does not need to change given fluctuating uncertainties and is represented in Figure 7.1 by some performance boundary in which it operates. This boundary cannot change once the system is deployed. Adaptability is where the system is able to change to maintain a known performance criteria and all system changes must be known at the time of deploying the system. For example, in a chemical plant, the system may change between feedstock to maintain output. The available changes to the system must be known when designing the system, however. In this case, each individual feedstock acts as a robust performance bound, and adaptability serves to switch between the options. Combining both properties, the total performance bound found from the aggregate of all initial designs give an initial robust bound which is known at the time of deployment. Flexibility, allows the system to change the performance boundary once the system is deployed and gives revised robust bounds. Taking the case of the chemical plant, this could be the introduction of new types of feedstock or upgraded processes which change performance. The conceptual model of resilience relating these three properties is shown in Figure 7.1.

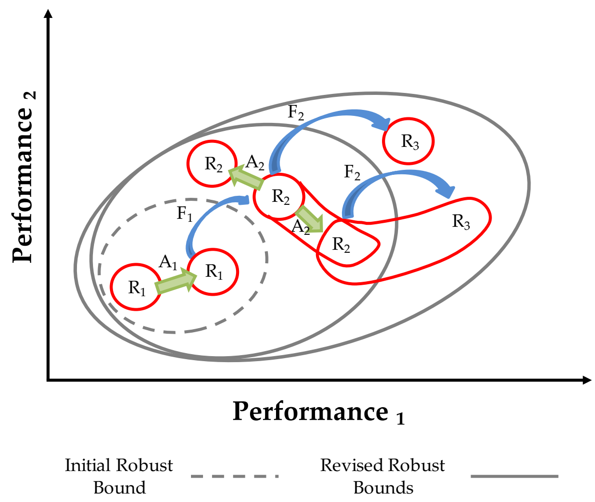


Figure 7.1. Conceptual model of resilience and relationship between properties

This conceptual model has been helpful in differentiating and understanding the relationship of the terms that have been often associated with resilience. Semantic difficulties still arise between adaptability and flexibility, however.

While useful as a model, more thought should be taken in applying this across domains since not all systems need to be robust, adaptable and flexible simultaneously. For systems, engineering or otherwise, that do not have growth in uncertainties and do not need to upgrade over time, a robust solution may suffice to be resilient such that it ensures both short term and long term success and this perspective may not be so useful. Equally, a system may not necessarily be adaptable, but could be flexible allowing for upgrades over time. Although all three properties have been found to contribute to resilience, there may be cases where a subset may suffice to ensure long term success and the model should not suggest that all three are necessary for resilience. This led to the conceptualisation of an initial robust bound which represents the total system performance boundaries at the time of deployment and simplified the analysis so that the task was to understand the performance boundaries at the time of deployment and how the system should evolve over time.

The key challenge of this work distilled from the conceptual model was therefore to understand the initial performance of systems and how a system should upgrade over time. Thus, there exists a trade-off between the two strategies: a system can be made with increasingly large redundancies but at some point this will become impractical, and instead, a flexible approach would be more cost efficient. As such, given a set of technology options each with some robust bound, this work explores which options should be deployed, when they should be upgraded and the order of the upgrades given a set of conditions. It may be the case that, under some conditions, it may be better to invest into large capacity technologies with enough redundancy to accommodate any expected fluctuations, or in other scenarios, the ability to upgrade depending on demand could be more efficient.

In order to facilitate these explorations and understand this trade-off, a support method was developed and applied to two case studies. Confidence in the support method was established by first applying the model to an existing study of a Waste-to-Energy system in Singapore with costings data on the upgrade process. The model was then used with BT to assess whether these results could also be found in industry. In both cases, the demand was assumed to be the major uncertainty and that resilience sought combinations of robustness and flexibility to maximise the ENPV of the system. The initial capacity and maximum number of upgrades served as proxies for robustness and flexibility respectively. The results of these parameters against ENPV for the Waste-to-Energy system is shown in Figure 7.2 The resulting plots from the BT case are similar.

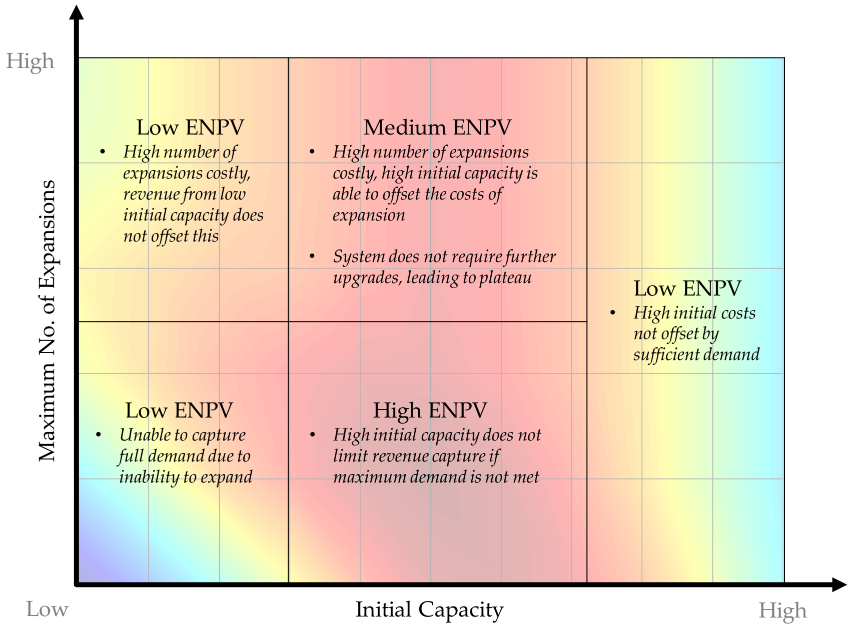


Figure 7.2. Summary of insights over ENPV surface

When plotting these parameters against ENPV, there was indeed some trade-off surface that suggested that there was the need for flexibility in addition to robustness as shown by the diagonal gradient in the bottom left of the plot. This indicates that as the initial capacity is decreased, there needs to be more number of upgrades to compensate. At first it may be expected that this diagonal slope on the bottom left would also have a matching decline diagonally where there are many upgrades and high initial capacity. That is, if there is a similar demand, but excess capacity, the inefficiency from high initial cost and upgrade costs would lead to a lower ENPV diagonal on the upper right. Instead, the trade-off boundaries are orthogonal to the axes on the right hand side of the plot, running from top to bottom. The implementation of decision rules meant that the expansion, while possible, did not need to happen if there was insufficient demand, thus maintaining the ENPV. More specifically, the “maximum number of upgrades” was used as opposed to just the “number of upgrades” to highlight the benefits of the decision rules. Without the decision rules, a more defined Gaussian function would be expected where the system is forced to expand despite insufficient demand. Furthermore, it is seen that the highest ENPV, shown by the red, is found where there is an initial capacity that matches demand and with one expansion. On the left hand side of this high ENPV area, the low capacity of the system meant that the demand was not fully converted to revenue while having too large a capacity, shown on the right hand side of the plot, there may not have had sufficient demand to maximise capacity. Where there were a lot of upgrades towards the top of the plot, the extra revenue from expansion may not have been enough to negate the cost of expansion.

This surface supports the idea of a trade-off between robust and flexible strategies: with a higher initial capacity (robustness), fewer upgrades (flexibility) are needed. This supports the hypothesis that designing engineering infrastructure systems with resilient strategies such as robustness and flexibility are useful in maximising ENPV. Furthermore, the surface allows decision makers to understand where different strategies may lead to the same outcome as well as visualising the trade-off between different approaches. As such, these surfaces form a major contribution of this work and the shape of these surfaces aid in understanding how resilience is affected by robustness and flexibility. This, to the author's knowledge, has not been discussed before in resilience literature and valuable in addressing resilience in engineering design.

7.2 On Modelling Resilience

The second contribution of this work involved synthesising the support method for modelling and assessing resilience. To this end, a substantial effort was spent in understanding the current state-of-the-art in research to give requirements outlining how these methods could be improved so that a novel contribution could be made through this work. This is especially important so that the final support method could be validated and verified to ensure that it meets requirements and that it is fit for purpose. Initial discussions with BT led to an interest in the theme of resilience and upon searching the literature, resulting in a conceptual model of resilience, it was apparent that there needed a strategic view of resilience for infrastructure systems. This led to the development of an initial reference model using the Least Squares Monte Carlo method adapted for a telecommunication case study. However, this method was not found to be sufficient and, while it could value the different options available to a system, the method's reliance on financial payoff was limiting. A new, more comprehensive, approach was needed to model the larger system, driving the synthesis of the support method. This leads to the next set of research questions regarding the modelling of resilience and is presented in Table 7.2.

Given the business, conceptual and technical requirements for this work from Chapters 1, 2 and 4 respectively, the design for flexibility framework was adapted to 1) incorporate Bayesian Networks in order to model decision rules and evaluate options and 2) adapted for resilience analysis by examining the

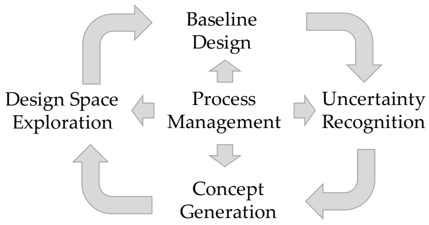
Table 7.2. Research Questions: Modelling Resilience in Engineering Infrastructure Systems

Modelling Resilience in Engineering Infrastructure Systems	
RQ3	How can resilience in engineering infrastructure systems be modelled?
RQ4	How can engineering design strategies be used to achieve resilience in engineering infrastructure systems?

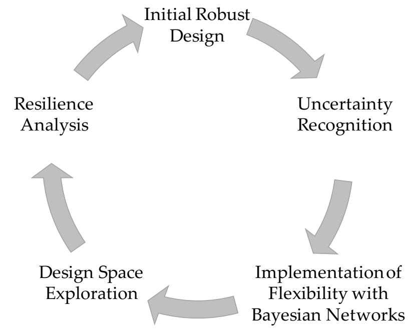
effects of drift and volatility in demand on the upgrade strategy. The original framework comprised of a five-phase approach: baseline design, uncertainty recognition, concept selection, design space exploration and process management. The first phase, baseline design, models the benchmark case where there are no modifications allowed on the system and thus was akin to modelling a robust model with no upgrades. Uncertainty recognition involved identifying as well as simulating the main sources of uncertainty and was done via geometric Brownian motion as per the original framework. Originally, the third phase was used to identify where flexibility could be implemented in a system and the options that were available for upgrade. Here, such options have been assumed to be found and instead Bayesian Networks were added to model the decision rules and select between the different options. This was necessary given the technical requirements to account for more sources of uncertainty. The fourth phase used in this work is similar to the original in optimising for the best strategies. Finally, resilience analysis was completed as the fifth step as opposed to process management. In order to satisfy the business and conceptual requirements, this last step further involved understanding how uncertainty affects which technologies that were to be deployed and when these would be upgraded. The original framework and the one used for this work are shown in Figure 7.3. Reflections on these two contributions are given in the next two subsections.

7.2.1 Implementation of Flexibility with Bayesian Networks

The first contribution of the novel support method pertained to modelling the decision rules for flexibility through Bayesian Networks. These were chosen particularly for the ability to account for a broader scope of uncertainties, both qualitative and quantitative, when deciding whether to pursue the flexible option.



(a) Original flexibility framework developed by Cardin (2014)



(b) Framework for novel support method

Figure 7.3. Comparison of original and new framework

Furthermore, Bayesian Networks provide an intuitive interface for decision makers to visualise the dependencies between variables and can also exploit prior domain knowledge from experts.These properties of the Bayesian Network allows the technical requirement to be better satisfied than with the Least Squares Monte Carlo approach. The implementation of Bayesian Networks was first tested and compared to an existing study by Ziqi (2017) which investigated the value of flexibility in Waste-to-Energy systems in Singapore. The original work used IF statements to model decision rules and these were replaced by Bayesian Networks here to decide whether to expand capacity and if in a decentralised manner, which sector to expand in. Simulated results were similar to the existing study and gave confidence as well as experience in building Bayesian Networks for a further extended study with BT. A much more detailed Bayesian Network was developed for the BT case where the tasks was to understand what and when to install technologies given some observations on the system.

The advantages of the Bayesian Network were most evident when working with industry experts: the graphical structure between the variables were intuitive and engaged participants quickly. Netica, a software for building Bayesian Networks, was especially useful in visually presenting to stakeholders and the impact of the observations propagation across the system could readily be shown. While development of the software for the model took around 6 months, the actual data gathering from experts was done over 3 workshops, with each lasting no longer than 3 hours. This made it a relatively efficient method of data gathering and brainstorming the variables to be incorporated. The variables and dependencies were elicited by structuring discussion around uncertainties that affect the problem, the system to be modelled, the available technology options and the performance metrics as detailed in Chapter 5. This was useful to guide the process of building the Bayesian Network, but care should be taken to only include variables that are of relevance to avoid having too complex a Bayesian Network. In such a case, divorcing, a technique to reduce the number of inputs to a node, can be used to simplify the Conditional Probability Tables (CPTs). Furthermore, dependencies should represent a one-way casual flow such that there are no cycles in the models. In the initial models it was found that some links connected performance nodes to uncertainty drivers. For example, while having a better customer satisfaction may in turn drive higher demand, this turned into a cycle which cannot be modelled through Bayesian Networks. Instead, the performance nodes have to be the end leaf nodes of the network. When brainstorming variables to be considered in the model with participants, there transpired natural groupings of physical and business factors of the system. These were accounted for relatively easily by the Bayesian Network and allowed for the mixing of qualitative and quantitative factors. That said, strictly speaking, qualitative variables were enumerated in the coding implementation of the model.

The variables and dependencies were relatively straightforward to elicit and the major challenge, however, was building the CPTs which encoded the probabilistic relationships. For nodes with few dependencies and states, experts were asked to fill these in manually on a scale where high, medium and low are 90%, 50% and 10% respectively. Whether this, or other scales should be used such as 80%, 50% and 20% should be investigated. Furthermore, due to time constraints, the workshops were held with multiple participants but ideally these values should be filled in individually before being aggregated to reduce bias. Another challenge was generating CPTs for larger nodes, such as the "Technology Option" classifying node which required 12,800 values and was impossible to fill manually. Instead, a key based on expert insights was used to map values from the parent node to the child node and the CPT was generated algorithmically. While this worked, a more robust algorithm should be considered to generate more accurate distributions. Furthermore, if distributions were not sufficiently distinct, it meant that the classification was not clear cut. For example, in the "Technology Options" node, if the technology characteristics were not pronounced enough, the situation where each option was used is difficult to classify. Thus, while experts gave initial scores for the variables, further fine tuning of the model was required by the author to give the correct behaviour of the Bayesian Network model. This manual refinement of the CPT also allowed thresholds to be set and for options that could not exist, such as downgrades in technology, the CPT had to be manipulated to give 0% probability for such cases. On the other hand, the CPT could also be used to threshold and change the likelihood that the technology be upgraded. Another pertinent problem is the discretisation of continuous variables which still remains a challenge and an active area of research. If large intervals are used, there is more information loss, while on the other hand, if too small an interval be implemented, there become more states to be computed through the CPT. This is especially a problem if there is a large range and spread of values. Therefore some insight into the range of values for discretisation has to be made so that observations can be made and fall within the range of states.

In the context of resilience, Bayesian Networks were successfully implemented to choose between technology options given a range of observations on the system and were used to satisfy the business and technical requirements. The technique was able to classify technologies following decision rules from domain experts for different areas of Cambridgeshire and the results could be plotted over time. The ability to capture expert knowledge and also visualise findings made it a valuable tool in this work and should be considered for other case studies. Bayesian Networks, to the author's knowledge, have not been used to model resilience in this way and would be suitable in exploring whether a system requires flexibility. Moreover, the decision rules captured here have been assumed to be optimal. However, it may be that other decisions rules could lead to higher ENPVs and an algorithmic method of optimising the CPTs would be a useful further insight.

7.2.2 Resilience Analysis

The second technical contribution of this work involved adapting the design for flexibility framework for resilience analysis whereby the effects of changing the volatility and drift of demand as well as expansion cost on the technology choice, timing of upgrade and design strategies were examined. Volatility pertains to the spread of projected demand and thus has been used as a proxy for uncertainty while drift represents the growth rate of the demand. Since resilience was mapped to the maximisation of ENPV, naturally the monetary cost of expansion also became consideration when deciding between robust and flexible strategies.

The effects of these parameters were investigated in both the Waste-to-Energy and BT case studies. For the first case study modelling a Waste-to-Energy system, the decisions related to whether the system should be upgraded and in the event that it should, in which sector to expand capacity. These were unit expansions such that the capacity would expand linearly. On the other hand, the BT case considered switches between fibre optic technology as well as throttling and thus the capacity could step increase. When varying volatility in the Waste-to-Energy system, the wider spread of demands thus resulted in a larger range of years where the system was upgraded. These upgrades also favoured a centralised expansion with increasing volatility, reflecting the fact that all thresholds need to be surpassed simultaneously for decentralised expansion to take place. This was different in the BT case where increased volatility made the system increase capacity earlier to higher capacity technologies after triggering the decision rules. This can be shown in Figure 7.4 for the BT case where the technology paths are steeper in gradient as the volatility is increased and indeed, some technologies are skipped. While the increased volatilities lead to some technologies being skipped, it should be noted that the end technologies after 15 years remain the same.

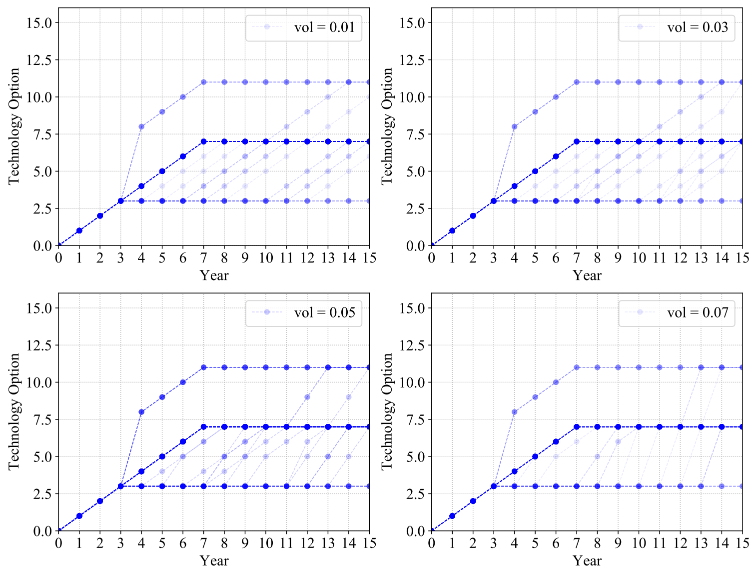


Figure 7.4. Technology upgrade paths with varying volatility

Furthermore, the Waste-to-Energy system is only able to increase capacity in unit steps, whereas the BT case allowed to switch between technologies to give step increases in capacity so that high capacity technologies are able to capture all of the demand. In terms of ENPV, the inconsistent demand from higher volatilities and stringent upgrade rules meant that all the demand could not be captured effectively in the Waste-to-Energy case, resulting in a reduction in ENPV. For the BT case, however, this early trigger to high capacities allow for a wider range of demands to be captured and thus actually increases the ENPV value as shown by the surface plots. That said, high volatilities are not the same as sustained demand and consideration should be given to situations where spikes in demand could trigger the decision rule to upgrade, but not have the continued demand to make use of the upgraded capacity. This further leads to work in simulating scenarios which do not have constant volatility and drift.

The drift, or growth rate, of the demand is also varied to investigate the effects on the technology upgrade process. For both cases, as the growth of demand increased so did the need for higher capacity of the system and therefore the need to upgrade earlier. This is intuitive and as expected. However, when varying drift for the BT case, there was a jump in ENPV when the high growth demand was sufficient to make the Bayesian Network switch straight to the highest capacity technology, FTTP, and thus capture a larger proportion of demand. The Waste-to-Energy system, could only upgrade in unit increases so that there was a smoother increase in ENPV with more upgrades. These insights are summarised below.

Table 7.3. Technology considerations for Waste-to-Energy system with uncertainty

	Waste-to-Energy System	
	Increased Volatility	Increased Drift
What to expand	Main site	Non-main site
When to expand	Expansion in larger spread of years	Expansion earlier
Order of expansion	Expands linearly due to model design	Expands linearly due to model design

Table 7.4. Technology considerations for BT case with uncertainty

	BT Case	
	Increased Volatility	Increased Drift
What to expand	High capacity technology (G.Fast/ FTTP)	High capacity technology (G.Fast/ FTTP)
When to expand	Expansion happens earlier	Expansion happens earlier
Order of expansion	Skips to high capacity technologies	Skips to high capacity technologies

In terms of design strategies, the effect of volatility, drift and expansion cost on the shape of the surface plots are examined. Volatility had little effect on these surface plots. There were lower ENPVs in both cases and flattening of the plotted surface as the demand was spread over a larger range, but the optimal design strategy to maximise ENPV did not change. However, in the BT case the higher volatility demands triggered an early upgrade of the system and suggests that having a higher robustness or initial capacity could be considered to capture all the demand without need to upgrade. The effects of increasing drift are consistent across both cases and it is found that, as expected, more upgrades, and thus flexibility, is deemed necessary to keep up with increasing demand. It suggests and supports the finding from the literature review in Chapter 2 that, in order for systems not to just survive but thrive, robustness is not enough and that if there is growth in demand, the optimal configurations have at least some flexibility. Having a large initial capacity to account for future growth may not yield the highest ENPV, and could be risky if the capacity is not met which is similar to the argument in studies by de Neufville and de Weck. This is shown by the drop in ENPV on the right hand side of Figure 7.2.

All the initial results suggested that some flexibility would provide better ENPVs than a purely robust solution with no upgrades. This is of course the widely held view in the design for flexibility and that flexibility not only allows to expand for extra capacity, but also mitigates risk in the case that demand is not as forecast. This trade-off between robustness is clearly shown on the bottom left of Figure 7.2, where it is found that as initial capacity increases, the number of upgrades needed decreases. This is as expected since essentially the two parameters combine to make up the capacity for demand. However, from a theoretical point of view, there must be some situation, perhaps not realistically, that a robust system would perform better. Since flexibility seemed to be always necessary in these experiments with various volatility and drift, the switch in strategy from a flexible solution to robustness must depend on another parameter. Attention was therefore turned to the expansion cost of the system. For both cases, as the cost for each expansion increased, it was found a robust system with no upgrades would yield a higher ENPV after some threshold. The shape of the surface also changes and a ridge appeared where there would be optimal robustness. As such, it can be seen that while volatility and drift changes the configuration that yields the highest ENPV, the switch between robustness and flexibility is determined by the expansion cost. These insights are summarised in the following table.

Table 7.5. Design considerations with uncertainty

Design Strategy		
Volatility	Increased volatility triggers upgrade for capacity to match demand such that all demand is captured.	Consider Robustness to capture fluctuations in demand
Drift	Increased drift triggers more upgrades.	Consider Flexibility if demand grows over time
Expansion Cost	Switches between purely robust strategy and hybrid combination of both	If expansion cost high, consider robust solution; If expansion cost low, consider flexible solution

7.3 On Achieving Resilience

Having developed the conceptual model, support method and obtaining results, the final question is whether this work was appropriate in exploring "The Design of Resilient Engineering Infrastructure Systems" from the lens of engineering design. To this end, the Design Research Methodology was followed to maximise the success of this project and ensure not only suitable questions were asked, but also answered effectively. From an engineering design perspective, this emphasised the need for both understanding and synthesis which have been discussed in the previous two sections of this Chapter. The suitability of the developed methods are now examined through the final two research questions given in Table 7.6 and addressed in the following subsections respectively.

Table 7.6. Research Questions: Achieving Resilience in Engineering Infrastructure Systems

Achieving Resilience in Engineering Infrastructure Systems	
RQ5	How well does the support method meet requirements for designing resilient engineering infrastructure systems?
RQ6	How fit for purpose is the support method in designing resilient engineering infrastructure systems?

7.3.1 Success & Validation

A crucial part of research requires not only the right questions be asked, but also an evaluation of whether the questions have been duly assessed and answered. A substantial amount effort was put into obtaining business, conceptual and technical requirements so that the support method could be verified. Business requirements were elicited through early discussions with BT, as presented in Chapter 1, and are:

Business Requirements

- To understand what technology options are most appropriate for different areas of Cambridgeshire
- To understand when technology options should be changed for different areas of Cambridgeshire
- To understand the optimal order of change for each of the technologies options for different areas of Cambridgeshire

This work addressed this by incorporating Bayesian Networks into the design for flexibility framework so that, based on some decision rules and uncertainties observed on the system, different technology options would be selected over time. For the Waste-to-Energy case study, the Bayesian Network could recommend whether the system should expand or not, and in the event that it should, which sector should be upgraded. In the BT case, different fibre optics technology options were classified given observations of the area at each time slice. These decisions could be modelled over time to understand what and when these systems should be upgraded. The results of this work were also presented back to BT on numerous occasions to iterate and validate the model. Although real data should be input to the model and further refinements should be made, the model has been able to capture similar decision rules as the experts and as such, satisfied the business requirements.

Through the literature review in Chapter 2, a conceptual model eluded to the strategic needs of resilient engineering infrastructure systems. Specifically, there was a need to better understand the robust and flexible strategies for resilience and hence the conceptual requirements became:

Conceptual Requirement

- To understand the trade-off between robustness and flexibility in designing resilient engineering infrastructure systems

Using the novel support method developed through this work, this trade-off could be investigated and was demonstrated in both of the case studies. The results of the model, as discussed in the previous sections, were as expected and while there were no major surprises, the resulting surfaces were intuitive and also valuable in prompting discussion. The trade-off between robustness and flexibility could be identified but perhaps more importantly these plots could be used as a map for organisations to understand the upgrade process. For example, given some demand projection with drift and volatility, and if the current/initial technology was copper, the value of upgrading to FTTP compared to G.Fast could be determined. In the Waste-to-Energy system this could also aid the discussion in understanding, for a given demand projection, what is the initial capacity and number of upgrades to maximise the ENPV of the system. Thus the model not only serves to output results but can help decision making through what-if scenarios and assess the impact of different investments. Indeed, upon presenting results back to industry, this work has gained substantial traction and coupled with the use of Bayesian Networks which have been intuitive for stakeholders, the support method has prompted explorations of further work in other areas of the organisation.

In order to gather technical requirements, a preliminary model using the LSM method was developed in Chapter 4 to explore the current state-of-the-art and the limitations of extant methods. It was found that, while the LSM method can be used to value different technology options, its financial nature based on financial options theory made it difficult to account for uncertainties which may not be intuitively mapped to monetary value such as customer satisfaction. This is especially important for infrastructure systems which are often socio-technical and have organisational considerations. The technical requirement for the novel support method was therefore:

Technical Requirement

- To consider a holistic view of engineering infrastructure systems by capturing more types/number of uncertainties acting on the system

The final technical requirement was addressed by using Bayesian Networks to capture the decision process as well as accounting for both qualitative and quantitative data. It has been advantageous in being able to capture expert knowledge across domains of BT efficiently. The model will most likely be biased in that it is a representation of the view of the system by a select group of experts. However, with more time, the Bayesian Network could incorporate more variables with more data to present a more objective view. A further criticism of the LSM method was that decisions were based purely on financial payoff. While resilience could also have been measured and maximised through a number of metrics such as time for recovery, the amount of disturbance that a system can withstand *etc.*, the ENPV was chosen for business tangibility since almost all areas of the organisation can attribute to financial metrics. Even the time for recover in other case studies, would have some financial impact on the system. However, it should be noted that the choices between technologies modelled by the Bayesian Network, was not necessarily based on cost as in the LSM model, but by the other parameters in the physical system or relating to the business, and the ENPV was calculated after these choices were made. Furthermore, the advantages of this framework is that the component parts are well established: ENPV analysis is prevalent in finance, Brownian motion has been well studied in natural phenomenon and Bayesian Networks have a strong probabilistic foundation. This makes it approachable for other researchers in applying this to their own case studies and both the ENPV as well as Bayesian Networks are able to capture considerations for a range of domains that require this specific view on strategic resilience.

From this review, it seems that the model has been successful in satisfying and verifying against the requirements set by earlier explorations in literature. The results have been presented back to industrial and academic stakeholders with positive feedback. That said, these results and the model pertains to a particular, strategic view of resilience and further studies are required to understand where these assumptions – for example whether all three robustness, adaptability and flexibility are simultaneously required for resilience – do not hold. This is discussed in the following subsection.

7.3.2 Limitations of Support Method

While the requirements of the support method have been met, it is important to understand how this framework sits in the wider landscape of resilience and how it can be improved. Coming from engineering design, a two pronged approach was adopted where this work aimed to contribute to both conceptual and technical understanding. First, the concept of resilience taken here has been more of a strategic view compared to the traditional operational risk models found in engineering and organisational management. This was mapped to the engineering design properties, namely robustness and flexibility. Robustness alone could be seen as similar to the models in engineering resilience where the objective is not to fail under stress. Here, this is complemented by recognising that in some systems, being robust, while important, is insufficient. This is especially true for infrastructure systems where long lifecycles may subject the system to changing requirements and it is difficult, and sometimes risky, to build such systems based on some forecast. Surely then, if the objective is to minimise long-term risk, upgrades and flexibility should also be considered in the conversation of resilience. There are many studies which mention different terms that effect resilience and perhaps it depends on application.

Here, the developed support method is able to certainly maximise the ENPV through assessing the initial capacities and the number of upgrades. Whether resilience can be assessed through mapping this to ENPV is open to the interpretation of resilience. If resilience is taken to be a strategic combination of robustness and flexibility, this model uses the initial capacity and maximum number of upgrades as proxies respectively. It would be interesting to understand how this could be mapped onto a social system such as for psychological resilience in teams or in disaster management. Perhaps robustness and flexibility in such a case could pertain to the strength of relationships between individuals. However, for the case of infrastructure systems, the main considerations were the demands on the system over time and ENPV calculations are useful in accounting for inflation over the long lifecycles of the system as well as giving business tangibility to the model. The use of ENPV is also generic enough so that this approach can be applied and analysed in other (infrastructure) systems. It is recognised, however, that depending on application, other metrics may be more useful and that it depends on the stakeholders of the project. For engineering infrastructure systems, these concepts and strategies seems to hold, but given the far reaching applications of resilience, more work needs to be done in differentiating between the success metrics in each domain.

The technical support model itself was apt in eliciting the decision rules and did indeed find a trade-off between robust and flexible strategies. While the business requirements have been met and the Bayesian Network has been able to recommend the technology options, the main limitation is that their construction remain subjective, almost an art form. These would especially be influenced by the participants who built the models with their own specific interests and view of the system. It would therefore be useful to further validate these outputs with data and comparing the structure of a Bayesian Network learned from data and the one generated with experts. That data, however, could be difficult to source given that this work aims to consider a more holistic view of the system as per the technical requirements. Furthermore, integration of different data sets could be a problem. However, this is a problem of many quantitatively based models and knowledge extraction remains a challenge. That said, this also highlights where the Bayesian Network approach excels and with a limited amount of time, a network was built that could capture expert knowledge of the system to recommend upgrades for the system with reasonable results. Further work through optimisation of the conditional probability tables could examine whether the decision rules obtained from experts are in fact the best decision rules to maximise ENPV . Resilience literature has also revolved around disaster management which has not been a primary focus here. There has been explorations to understand the role of volatility in demand but otherwise, both demand and volatility were simulated to be invariant over time. It was seen that spikes in demand induced by high volatility led to the decision rules making more upgrades. However, perhaps smarter decision rules could be implemented such that upgrades are only pursued if there is a sustained demand. Furthermore, other sources of uncertainty, such as competition, can be and should be explored with the Bayesian Networks.

7.4 Summary

This chapter discusses the developed support method with respect to the Research Questions defined in Chapter 1 and evaluates the contribution of this work. From an engineering design approach, it was important to improve both understanding and synthesise a support method. The definition of resilience derived from the literature review, where resilience requires the combination of robustness and flexibility, was demonstrated through the application of the support method to two case studies. A trade-off surface between the two design strategies existed and thus supports the definition from the conceptual stages of this work. The implementation of Bayesian Networks to better consider a holistic view of the system allowed for both quantitative and qualitative uncertainties to be examined and was also useful in engaging stakeholders due to its graphical interpretation. Resilience analysis involved understanding how the system behaves under different drifts and volatilities. The technologies and the timings of investment could be determined from this model and the greater utility came from visualising the solution space as a surface by plotting the ENPV against initial capacity and the maximum number of upgrades.

Upon reviewing these questions, it is suggested that this framework is able to assess resilience for this specific strategic view in infrastructure systems. The use of ENPV allows for this framework to be applied in other case studies where the stakeholders may be interested in the business case of resilience and the long term strategic view of the system. The novel support method presented in this work is thus appropriate in combining the short term view, modelled through robustness, and the long term perspective, modelled through flexibility, to maximise ENPV for a system's lifecycle.

Chapter 8

Conclusion

This work aimed to explore "The Design of Resilient Engineering Infrastructure Systems" which led to a journey of discovering the characteristics, definitions and challenges of resilience, the engineering design approaches to embed resilience into engineering infrastructure systems as well as ultimately synthesising a support method that would bring novel contribution. As such, two major contributions formed from this work: a conceptual model of resilience for engineering infrastructure systems and a technical model to understand the trade-off between robust and flexible design strategies. The insights gained from these investigations are summarised and concluded in this final chapter with respect to the hypothesis and objectives of this work. Key findings are evaluated and future work directions are also presented.

8.1 Key Findings and Contributions

Underpinning this work is a design led approach summarised by Simon (1988) as, "Everyone designs who devises courses of action aimed at changing existing situations into preferred ones". The task of this work from a research perspective is to therefore devise a course of action to better understand how engineering infrastructure systems can be instilled with resilience. To this end, the Design Research Methodology (DRM) was followed which emphasised the need to not just understand the concepts but to also synthesis a novel support method which can be used to address the research gap. This has been a useful methodology to follow due to the applied nature of this project and ultimately aids in developing a deliverable with industrial impact.

Following the DRM, Chapter 1 and 3 involved research clarification to understand the task at hand. First initial discussions were held with BT, the industrial sponsor of this work, and academic group to understand the recent challenges faced by both parties. This led to the theme of resilience and business requirements which sought to understand what and when to invest in various fibre optic technologies for resilience. However, the term resilience has been popular in a number of domains and context needed to be established for engineering infrastructure systems. As such, a broad literature review, initiating the Descriptive Study I of the DRM, spanning engineering, organisational management and ecology was conducted. This established three characteristics to be necessary for resilience: absorbing disturbances, adapting for change and thriving for the future which were mapped to engineering design strategies of robustness, adaptability and flexibility respectively. For engineering systems, a significant number of studies have looked into using redundancy and adaptability in keeping systems operational and maintaining performance despite disturbances. However, while these factors are necessary, they are not sufficient for resilience as defined from the literature survey and a less widely held, but nonetheless important view especially for infrastructure systems given the long lifecycles, was found to be also needed. Inspired by ecological literature, and now also becoming more recognised in management literature, resilience should also mean that the system should be able to "thrive" into the future. While certainly the inability to maintain operational performance in infrastructure systems such as telecommunications would be disastrous, a strategic view of how to continually provide value add and upgrade the system is also critical. As such, resilience can be thought of keeping the system operational as demands and requirements evolve over time. A conceptual model was developed to visualise this as a string of upgrades to the system over time where each upgrade or design has some robust bound – incorporating both robustness as well as adaptability since they serve to maintain normal operations – and flexibility which is used to move between the different designs. This conceptual model is the first contribution of this work and serves as the foundations on which to build the support method. Further investigations in understanding resilience in engineering infrastructure systems thus required an understanding of the trade-offs between the robustness and flexibility of the system. The insights from the conceptual model allowed the first two research questions to be examined and gave an improved understanding of resilience in engineering infrastructure systems.

The second contribution involved developing the support method to assess resilience and evaluate between designs. To this end, candidate models were sought from resilience literature to analyse for this view of strategic resilience. In particular, a quantitative approach seemed useful in assessing and comparing the value of many different designs. Furthermore, a quantitative method can aid in exploring the solution space to understand the current state of the system and find the parameters that can improve the system into a more ideal state. However, no solutions were found specifically for addressing this view of resilience in engineering infrastructure systems from resilience literature and other approaches were considered from engineering design. The design for flexibility and real options paradigm was deemed a good fit in addressing such challenges and a preliminary model utilising the Least-Squares Monte-Carlo (LSM) method was adapted for a telecommunications example to assess the basic model. While the method is able to value different options available for upgrade, the reliance on financial payoff was limiting and thus another method was needed which could consider a more holistic view of the system with a number of uncertainties. With this technical requirement, the Descriptive Study I phase of the DRM was complete and the novel support method was synthesised in the Prescriptive Study, as detailed in Chapter 5. To meet these requirements, the design for flexibility framework was adapted by implementing Bayesian Networks for flexibility and analysing resilience by varying the volatility and drift of demand. The performance of the system, and thus resilience, was mapped to the expected net present value (ENPV) which allowed comparison of infrastructure systems across different domains. This was applied to two case studies and the Bayesian Network implementation was able to recommend technology upgrades over time based on uncertainties observed on the system. The first case study was based on an existing study by Ziqi (2017) which modelled and optimised the expansion of a Waste-to-Energy system. This case was used to benchmark and verify the Bayesian Network approach synthesised in this work. The second case involved choosing between fibre optic technologies for installation with industry partner BT and served to gauge industrial interest in this work. For both cases, the initial capacity and maximum number of upgrades on the system served as proxies for robustness and flexibility respectively and thus the optimal strategies were configurations which maximised the ENPV of the system. It was found that indeed there was indeed a trade-off between robustness and flexibility and this could be shown in the surface plots thus supporting the hypothesis of this work. When varying the volatility and growth of demand, it was seen that the best strategies involved a combination of both properties. However, it was speculated that there exists some parameter which would change the strategy to favour only a robust solution without the need to upgrade. This was found in the form of expansion cost such that if there is a high expansion cost, a robust solution would yield a higher ENPV. These applications to case studies were part of the Descriptive Study II of the DRM and is useful to evaluate the industrial utility of such models. Through the technical support method, the third and fourth research questions were explored.

The final two research questions pertained to the verification and validation of the model respectively. To verify the support method, these were compared to the business requirements, gathered from industrial stakeholders in BT, conceptual requirements derived from the literature review and the technical requirements obtained from the preliminary model. While all three requirements were satisfied, the greatest utility of the model came in being a useful tool to prompt discussion and aid in evaluating what-if scenarios for decision makers. The Bayesian Network, although subjective, has proven to be advantageous in collecting data across the organisation and from experts warranting further consideration in future studies. The resilience analysis also was able to show the trade-off between robustness and flexibility with respect to initial capacity and maximum number of upgrades as well as the impact of volatility and demand on ENPV. Furthermore, the framework, being a combination of well-established techniques such as ENPV analysis, geometric Brownian motion, and Bayesian Networks allow for similar analyses to be conducted for other cases. The results were presented to both industrial as well as academic stakeholders and received positive feedback with interest in applying this work in other business units.

Given these results from answering these research questions, the objectives were met. These are listed below:

1. To develop a quantitative evaluation method for resilience in engineering infrastructure systems
2. To understand how design strategies affect resilience in engineering infrastructure systems
3. To providing guidance for decision makers to enable resilience in engineering infrastructure systems

The quantitative evaluation support method in the first point is detailed in Chapter 5 and the understanding of the design strategies as well as guidance for decision makers came from applying the support method to the case studies presented in Chapter 6. With the research questions evaluated and objectives met, the hypothesis, defined in Chapter 1 can be revisited to understand whether it stands. It was postulated that:

Hypothesis
Designing resilience into engineering infrastructure systems through engineering design strategies, allow such systems to better accommodate forthcoming uncertainties.

Through this work, it was indeed found that combining robust and flexible design strategies were beneficial in maximising the ENPV of engineering infrastructure systems under different demand projections. This hypothesis seems to be valid for the strategic view of resilience taken here and further studies should be taken to understand how this framework can be applied in other systems. In particular, improving resilience was taken to be the maximisation of ENPV which may not hold in more sociological systems, but for infrastructure systems which often involve many business units, the ENPV should be a useful metric. Demand was assumed to be the major uncertainty for both case studies and the role of the different design strategies are presented in Chapter 7. Although the results are not surprising, the developed support method does seem useful in providing decision makers a tool to understand the solution surface which visualises the trade-off between robustness and flexibility.

8.2 Future Work and Concluding Remarks

This work has provided interesting insights for the design of resilient engineering infrastructure systems and should be considered further to validate the approach in other domains. Conceptually, this work has presented another complementary view on resilience and incorporates the idea of longevity to resilience analysis. Traditional views of resilience, such as risk mitigation, can be captured through robustness in this framework, while the addition of flexible strategies allow for the long term perspective to be modelled. Future work would therefore involve investigating at what point should systems incorporate this strategic planning and perhaps not all systems require both robust and flexible strategies. Indeed, when exploring the impact of the expansion cost on the model, there were scenarios where the robust solution would suffice. As such, more consideration should be given to understanding how this conceptual model should be delimited for different systems.

On the technical side, a number of avenues may be pursued. For example, the obvious extension to the Bayesian Network is to validate the structure and probability tables through data. Furthermore, the Bayesian Network as-is chooses technology options not based on financial return, but on the physical and business characteristics of the system. An optimisation can be conducted on the conditional probability tables to investigate whether these are indeed the best decision rules to give the highest value and can be used to challenge business assumptions. Given the time constraints, simulations were run with the assumption that demand was the major uncertainty and other variables, such as competition, can be investigated further. A powerful property of Bayesian Networks are that inference can be conducted from cause to effect and also backwards, from effect to cause. That is, the current experiments seek recommendations for technologies given some observations on the system. This can be run the other way, for example, by observing the technology option that decision makers wish to deploy and inference can work out the initial requirements to give that recommendation. This model assumes the volatility and drift remains constant for the whole simulation period which is unrealistic for long time periods. The simulation could therefore be extended to incorporate volatility and drifts in demand that are not constant. This could further simulate shocks in demand being introduced into the system.

In summary, the main contributions of this work are:

- Synthesis of a definition of "resilience" for the design of engineering infrastructure systems.
- Development of a conceptual model which incorporates the traditional view of resilience focusing on risk and the need for a strategic perspective for engineering infrastructure systems.
- Development of a technical novel support method whereby Bayesian Networks were implemented to model decision rules and resilience analysis involved the maximisation of the system's ENPV through engineering design strategies of robustness and flexibility.
- Improvement in the understanding of how the engineering design strategies of robustness and flexibility may be used in the context of resilience in engineering infrastructure systems.
- Improvement in the understanding of how volatility and growth of demand could impact design strategies to maximise resilience.
- Visualisation of the resulting surfaces to aid decision makers in evaluating between what-if scenarios of the system.

To conclude, this work has examined “The Design of Resilient Engineering Infrastructure Systems” and set out to provide both an improvement in knowledge and the synthesis of a novel support method. Through the research questions, it offers a complementary extension to the existing view of resilience and a support method has been developed to demonstrate the added value of incorporating flexibility to this discussion. The results of analyses seem reasonably intuitive and have provided a better understanding of how resilience can be assessed for engineering infrastructure systems. The support method is valuable in allowing decision makers understand how robust and flexible strategies can impact the system’s lifecycle value and is useful in prompting discussion with regards to what-if scenarios. As such, this work has been successful in contributing to knowledge and provided a tool for analysing resilience in the context of engineering infrastructure systems.

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Appendix A

BT Workshop Booklet

UNIVERSITY OF CAMBRIDGE

The Design of Resilient Engineering Infrastructure Systems

Bayesian Network Workshop

Jonathan Mak

June 2017

Summary

The term resilience has become associated with uncertainty in many domains and there is now growing recognition that organisations need to become more resilient in order to not just survive hardship, but also thrive and prosper. How this is designed in to an engineering infrastructure system, however, is less well defined.

The purpose of this workshop is to partner with BT in understanding how resilience may be designed into an engineering infrastructure system using Bayesian Networks. This document therefore acts as a primer to resilience and Bayesian Network theory (sections 2 & 3) as well as detailing the tasks to be completed through the workshop (section 4) with members of BT.

In particular, the workshop guides the participant through the process of building a Bayesian Network for BT infrastructure systems and examines the uncertainties, interdependencies and design options of the system.

This information will be used in further PhD work to examine the implications of system design on resilience and to understand the components that should be built into the system to enable resilience.

Contents

1 Introduction

Large scale engineering systems, such as telecommunication networks and energy production plants, have relatively long life cycles and incur significant investments. As such, it is difficult to predict conditions and the evolution of technology over extend periods, let alone match supply and demand. In the case of a telecommunications company, it is not cost efficient to continually rebuild infrastructure, yet it has to somehow keep up with ever evolving technology and maintain satisfactory service to customers. Thus, in order to be successful, large scale engineering systems must be designed to stand the test of time, both technologically and financially.

This case study and workshop focuses on BT, a telecommunications company in the UK. The company is currently rolling out the NGA 2.0 project which delivers upgraded broadband networks for the United Kingdom. Key challenges involve:

- Determining where appropriate technology should be deployed so that customers have consistent access to high speed broadband.
- Ensuring the continual evolution of the network to support future technologies.

The aim is to use the concept of resilience to understand the balance between time, cost and uncertainty so that engineering systems withstands projected, near-future demands, yet allow for future change when it is necessary. While it is impossible to foresee all future evolution of technologies, a system may be designed to be flexible so that it *can* change when demand deviates from best estimates and be robust enough to handle expected fluctuations. For example, de Weck *et al.* conducted a study on the Iridium satellites which went bankrupt due to lack of expected demand and concluded that a phased deployment of satellites could have lowered the lifecycle cost by more than 20%. Although this may not have saved the project from bankruptcy, it could have significantly lowered the risk so that extra investments only occur when demand arises.

Similar analyses may be employed for large scale engineering projects, such as for NGA 2.0, in order to meet customer demand while mitigating risk and cost.

2 Primer on Resilience

Through a literature review detailed in other work by the author, 3 key characteristics were found to be fundamental for resilience in a system. These include the ability to:

- Absorb Disturbances
- Adapt for Change
- Thrive for the Future

In terms of engineering design, these are mapped respectively to the properties:

- Robustness
- Adaptability
- Flexibility

It is important to note that a subtle distinction is made here regarding the definitions of adaptability and flexibility. Although in literature and in common use, these are used interchangeably, here, these terms are demarcated by whether there is a change in requirements. In an adaptable system, following some perturbation, the system undergoes change to return performance to the previous normal or undisturbed state. This is a restorative change. Flexibility, on the other hand, allows the system to change for alternative performance levels and not necessarily to recover to the normal state. Flexibility therefore allows a system to change the system to attain different performances and hence "thrive for the future". These concepts are summarised in the following page.

CHARACTERISTICS	ABSORB DISTURBANCES	ADAPT FOR CHANGE	THRIVE FOR THE FUTURE
LIFECYCLE PROPERTIES	ROBUSTNESS	ADAPTABILITY	FLEXIBILITY
DESCRIPTION	System absorbs disturbances and maintains performance without needing to change any parts of the system	System automatically recovers from disturbances through some internal change of the system to maintain an acceptable, predefined performance*	System evolves to accommodate new requirements or opportunities given by some external decision maker
DESIGN	Typically designed into system through redundancy or buffering capacity	Typically designed into system through control/ feedback loops	Typically designed into system through modularity or platform design
SUITABILITY	Appropriate for the near-future or where uncertainties are predictable	Appropriate for the near-future or where uncertainties are predictable but changes to the system may be needed to maintain performance	Appropriate for the far-future where uncertainties are unpredictable
EXAMPLE	Bridge built with extra strength to withstand fluctuations in loading from wind or increased traffic	Aircraft system automatically responding to changes in flight conditions through control surfaces and maintaining stability	Standard USB interface used to accommodate new technologies

3 Bayesian Networks

Background

This BT case study aims specifically to understand how resilience affects the questions:

- Which technology options are most appropriate for different exchanges?
- When should the technology be switched?

Bayesian networks (BN) have been identified to be suitable for understanding the uncertainties and interdependencies of a system. Furthermore, advantages include:

- Inference can both be backwards and forwards (i.e. both cause to effect and effect to cause can be examined).
- Not all the data is needed in the network for results (explaining away).
- Both qualitative and quantitative uncertainties may be captured.
- BNs provide an intuitive decision support tool.

Although, the problem could be set as an optimisation problem, the main advantage is the ability to easily investigate both cause-effect and effect-cause relationships which allows for these questions to be answered more easily. Furthermore, stochastic optimisation using Monte Carlo methods can be computationally intensive compared to a Bayesian approach depending on the model.

BNs are directed acyclic graphs which represent sets of random variables and their conditional dependencies. For example, the probabilistic relationships between diseases and symptoms could be represented. The BN could then be used to compute the probabilities of the presence of various diseases given the observation of symptoms. An illustrative example of a rain/sprinkler system is given in Figure 1. The nodes represent random variables and the edges show conditional dependencies. A conditional probability table (CPT) shows the probability that the child node takes on for each of its different values for each combination of values of its parent nodes. For example, looking at the CPT of the sprinkler, the probability that the sprinkler is *True* given the rain is *False* is 0.4.

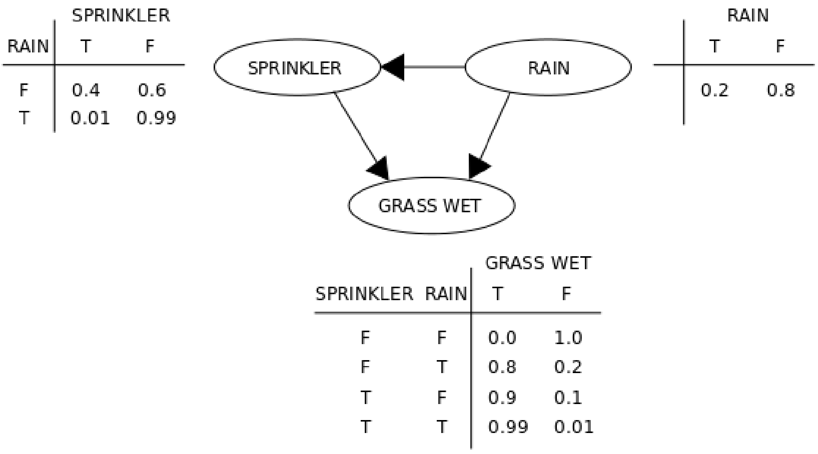

Figure 1 – Bayesian Network Example

Such a model can then be used to answer questions such as, "What is the probability that it is raining, given the grass is wet?" or finding $Pr(R = T \mid G = T)$. These probabilities can be inferred from the network using Bayes' Theorem which is defined as,

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Application for Resilience

While Bayes' Theorem appears mathematically simple, it has been used successfully in several domains such as medicine, engineering and for decision making. In applying this for resilient engineering infrastructure systems and BT, the BN may be structured as in the following figure.

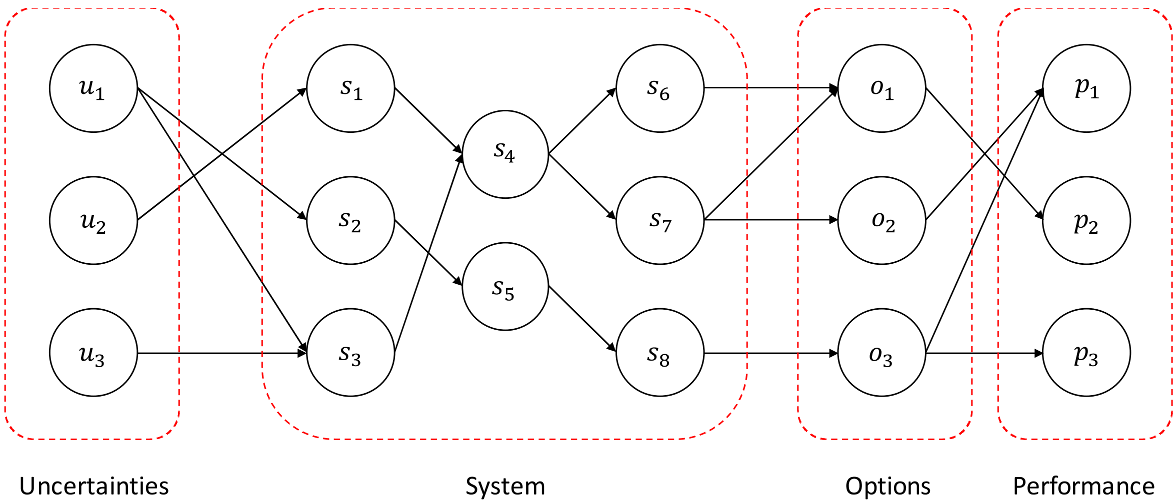

Figure 2 – Bayesian Network structure for engineering system

This example system is modelled through various layers. The uncertainty layer comprises input variables and requirements such as customer demand or cost of fibre. The uncertainties may then impact the actual system, such as the length of fibre or type of exchanges. The BN then has an options layer that classifies the type of technology that is most appropriate given the system configuration and uncertainty bounds. The chosen set of technologies also has a set of performances, such as bandwidth or latency, depicted by the final layer.

The advantage of the BN is that certain nodes can be observed and the impact propagated through the model. By setting uncertainties to values typical for certain exchanges, the most beneficial design option can be selected. Working the other way, by constraining the option type, the uncertainty profiles the option can accommodate can also be found. By comparing these profiles, the appropriate implementation of technology options may be found. This is shown by the following figure.

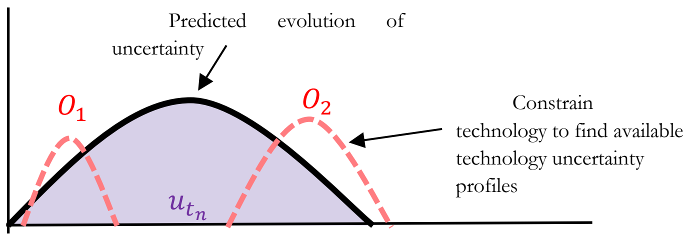

Figure 3 - Illustration of predicted and technology uncertainty profiles

This further allows the robustness, flexibility and therefore resilience of the system to be assessed.

Robustness

- Predicted evolutionary uncertainty profiles do not vary sufficiently to prompt change in technology.

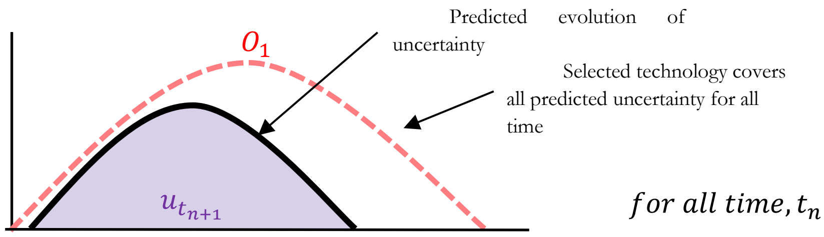

Figure 4- Robustness uncertainty profiles

Flexibility

- Predicted evolutionary uncertainty profiles vary with time and prompts changes in technology

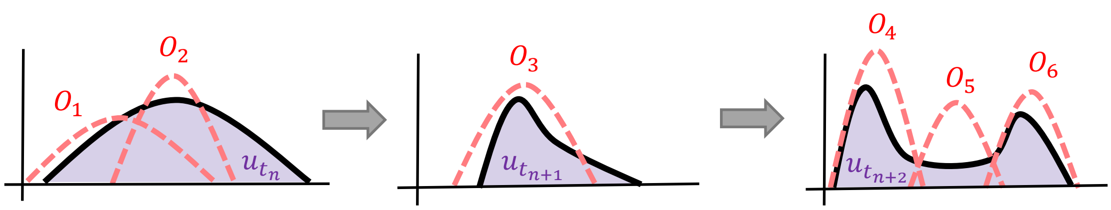

Figure 5- Flexible uncertainty profiles can changing technologies

Resilience

- The predicted uncertainty profile and the uncertainty profile from the technology options can be compared over time.
- Each technology choice also incurs a cost of operation C_{O_n} and investment cost C_{I_n} at time = n, (C_{O_n} > 0).

$$Resilience = \max \frac{\sum_{t=0}^{N} \frac{uncertainty\ profile\ of\ technology}{predicted\ uncertainty\ profile} * (C_{O_n} + C_{I_n})}{N}$$

For each time slice, this metric is > 1 where the technology options exceed the predicted uncertainty profile. This can also be seen as a robustness measure if the technologies do not change and therefore where this metric is > 1 also represents the tolerance/margins of the system**.** However for large scale infrastructure systems, the technology typically changes or evolves and so this metric can be used to optimise for the selection of technology options over time.

This allows for the incorporation of robustness and flexibility into one metric so that resilience can be measured. Robustness and flexibility are therefore different mathematical constraints that can arise in this metric.

Questions for Analysis

Once the model has been built, a number of questions may be answered using the model by posing a number of scenarios and constraints on the model.

Table 1 - Scenario List

	Question	Method
1	What technology options are most appropriate for different exchanges?	Observed characteristic uncertainties of exchanges input to the nodes and the appropriate technology option can be classified.
2	When should the technology be changed?	BNs allow for the technology to be constrained so that the inference works “backwards” to find the range of uncertainties that the option accommodates. By knowing the range of uncertainty, a projection can be made to predict when in the future the uncertainty profile may be exceeded and therefore when to switch technology.

3	What order of technology adoption should be deployed?	Given a number of technology options: • Not all technologies have to be deployed • There are transitions between technologies and therefore the optimal path can be found. By understanding when the technology should be switched from question 2, the optimal path between technologies can be found.
4	How robust and flexible should the system be?	There is substantial investment cost with each new technology. There may be the case that it is better to deploy a more robust technology than make multiple technology changes. Therefore, these can be compared with: • Robust case: hold technology constant • Flexible case: allow for technology change ⇨ Compare resilience metric of both cases

Verification & Validation

The model requirements and design should first be verified so that the correct model is built and the appropriate questions are posed. This addressed by the first part of this workshop.

For validation, the output of the model may be matched to existing design methods at BT and differences in design (number of similar designs), time and cost can be measured to establish the validation of the model. Furthermore, the technology options may be evaluated in terms of cost through NPV analysis. This will be future work after this workshop has been completed.

4 Workshop Task

This workshop comprises 2 parts: a semi-structured interview (approx. 1 hour) and a modelling task (approx. 3 hours)

Understanding NGA 2.0 Requirements & Questions (1 hour)

This initial part of the workshop aims to draw out the requirements for further work and verify the current model. A short presentation of the current model (15 mins) will be followed by requirements gathering. The functional requirements asks what questions we would like to answer (purpose of model/what is the problem) while the technical requirements asks how this should be done (questions on the model itself).

4.1.1 Functional Requirements (30 mins)

- What is to be modelled for the NGA 2.0 project?
- What does resilience mean to the NGA 2.0 project and how can it be applied?
- What are the most important design questions you need to understand for NGA 2.0? E.g.
    - Where should new technology be deployed/under which geotype?
    - How does the evolution of technology affect option choice?
- How appropriate are these questions/methods?
- What further questions (see § 5.3) may be useful to answer for NGA 2.0?
- What are the most important inputs/outputs needed to understand NGA 2.0?
    - Inputs: uncertainties, data types; outputs: performance, option choice

4.1.2 Technical Requirements (15 mins)

- How would you normally tackle this problem?
    - How long does this problem take?
    - What software/techniques do you use?
    - How many people does this take?
    - What are the limitations of the current models (if any)?
- What are the requirements of a “good” model?

    - How do you measure accuracy/quality of your current models?

Constructing the Bayesian Network (3 hours)

The second part of the workshop involves constructing the BN for BT's network. This is split into 4 phases corresponding to the 4 layers of the model. An existing model of the BT network has been developed previously and is used as a basis for this model. At this point, only the relationships between variables need to be established. The probability tables will be input after having built the model at the end of the workshop.

4.1.3 Uncertainty (30 mins)

The uncertainty layer of the model captures external variables of the system:

- What are the demands of the NGA network?
    - Customers?
- What other external factors affect the network?

4.1.4 System Interdependencies (30 mins)

This section models the system interdependencies which may be affected by the uncertainties. Please consider all dependencies even if it not a major in design e.g. the price of copper, may increase the cost of deploying copper wires, but other considerations (performance) may be more important.

- What are the interdependencies of the system?
    - Type of exchange → no. houses?
- How do the uncertainties impact the network?
    - No. of customer → type of exchanger?

4.1.5 Design Space (30 mins)

It is assumed that the current work focuses on the choice between fibre technologies FTTC, FTTP, G. Fast and Copper.

- What are the other network technologies for consideration (if any)?
- How do uncertainties affect the choice to technology?
    - No. of customers → technology?
- How does the system affect the choice of technology?
    - Type of exchange → type of technology?

4.1.6 Performance Layer (30 mins)

The performance of the technology type are evaluated in the performance layer. This could include the cost of implementation, performance metrics such as bandwidth or latency.

- What performance metrics are important for NGA 2.0?
- How do uncertainties affect the performance?
    - Cost of copper → cost of implementation?
- How does the system affect the performance?
    - Type of exchange → bandwidth?
- How does the choice of technology affect performance?
    - FTTC → latency?

4.1.7 Probabilistic Relationships (1 hour)

We look at the probabilistic change impact on each system.

Having built the model and established the respective relationships, the strength of the relationship is now input for each node. Suggestions for probabilities are given according to the following table:

Strength of Relationship	Value
High	0.9
Medium	0.6
Low	0.3

Verification & Validation

To ensure the work carried out is appropriate, a short survey after completion of this workshop and the analysis of result will be sent out.

5 Concluding Remarks

Thank you for your participation in this workshop.

This gathered data will then be used to propagate the model and answer the questions posed in Section 3.3 along with any other research questions that have arisen from the workshop.

Following this, the results of the analysis will be presented in July and your thoughts and comments on the model/results will be appreciated. This will take the form of a discussion after the presentation of results and a survey/questionnaire.

Should you have any questions, feel free to get in touch at: whjm2@cam.ac.uk

Many thanks!

Jonathan Mak
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CB2 1PZ

6 Appendix

BT NGA 2.0 Workshop Questions 2017

Functional Requirements
What is to be modelled for the NGA 2.0 project?
What does resilience mean to the NGA 2.0 project and how can it be applied?
What are the most important design questions you need to understand for NGA 2.0? E.g. o Where should new technology be deployed/under which geotype? o How does the evolution of technology affect option choice?
How appropriate are these questions/methods?
What further questions (see § 5.3) may be useful to answer for NGA 2.0?
What are the most important inputs/outputs needed to understand NGA 2.0? Inputs: uncertainties, data types; outputs: performance, option choice

Technical Requirements
What is the normal process of tackling this problem?
How long does this problem take?
What software/techniques do you use?
How many people does this take?
Are there limitations to the current models?
What are the requirements of a “good” model?
How do you measure accuracy/quality of your current models?

BN Modelling
Uncertainty
What are the demands of the NGA network? o Customers?
What other external factors affect the network?
System Dependencies
What are the interdependencies of the system? o Type of exchange → no. houses?
How do the uncertainties impact the network? o No. of customer → type of exchanger?

Design Space
What are the other network technologies for consideration (if any)?
How do uncertainties affect the choice to technology? o No. of customers → technology?
How does the system affect the choice of technology? o Type of exchange → type of technology?
Performance Layer
What performance metrics are important for NGA 2.0?
How do uncertainties affect the performance? o Cost of copper → cost of implementation?
How does the system affect the performance? o Type of exchange → bandwidth?
How does the choice of technology affect performance? o FTTC → latency?

Appendix B

BT Model Data

B.1 Cambridgeshire Exchange Data

Exchange name	Postcode	Latitude	Longitude	Serves Residential	Serves Non-Residential	Total Served	FTTC	FTTP	Virgin
Abbots Ripton	PE282PB	52.38551	-0.193170	292	38	330	Y	Y	N
Arrington	SG80HF	52.12086	-0.070540	997	61	1058	Y	Y	N
Benwick	PE150XQ	52.49413	-0.022480	432	32	464	Y	Y	N
Bottisham	CB59DU	52.22343	0.258273	1820	90	1910	Y	N	N
Buckden	PE195XA	52.29307	-0.254520	2336	82	2418	Y	Y	N
Burwell	CB50DU	52.27426	0.327478	3030	88	3118	Y	N	Y
Bythorn	PE280QN	52.36937	-0.449500	347	29	376	Y	N	N
Cambourne	CB37QG	52.21573	-0.076174	844	7	851	N	N	Y
Cambridge	CB23ET	52.20266	0.121950	24161	2026	26187	Y	Y	Y
Caxton	CB38PP	52.20845	0.094796	1949	68	2017	Y	Y	N
Chatteris	PE166NA	52.45433	0.048510	4437	216	4653	Y	Y	N
Cherry Hinton	CB13PR	52.18973	0.145250	16980	615	17595	Y	Y	Y
Cheveley	CB89DQ	52.22556	0.464800	1227	47	1274	Y	Y	N
Christchurch	PE149PG	52.54558	0.203860	405	42	447	Y	N	N
Comberton	CB37BS	52.18542	0.020556	2083	89	2172	Y	Y	N
Cottenham	CB48QS	52.22832	0.138590	2687	113	2800	Y	N	Y
Crafts Hill	CB38EL	52.24957	0.022382	2993	96	3089	Y	N	Y
Croxton	EMCROXT	52.22075	0.179539	407	33	440	Y	Y	N
Doddington	PE150TN	52.49596	0.067410	1708	54	1762	Y	Y	N
Elsworth	CB38LX	52.25557	-0.072336	451	39	490	Y	N	N
Elton	PE86RE	52.53113	-0.402180	721	47	768	Y	N	N
Ely	CB61AE	52.40168	0.261570	8868	502	9370	Y	Y	Y
Fordham Cambs	CB75NJ	52.31112	0.392780	1504	64	1568	Y	Y	N
Fowlmere	SG87QN	52.09513	0.078520	704	54	758	Y	N	N
Friday Bridge	PE140HJ	52.62236	0.164490	1335	46	1381	Y	N	N
Fulbourn	CB15DJ	52.18268	0.222039	1776	93	1869	Y	N	Y
Gamlingay	SG193JH	52.15534	-0.191310	1735	79	1814	Y	N	N
Girton	CB30LG	52.22389	0.090350	1773	52	1825	Y	Y	Y
Great Gransden	SG193AD	52.18601	-0.143350	664	52	716	Y	N	N
Guyhirn	PE134EB	52.60736	0.061170	435	51	486	Y	N	N
Haddenham	CB63SS	52.35769	0.151700	1743	52	1795	Y	Y	N
Harston	CB25PX	52.13701	0.077966	2659	112	2771	Y	Y	Y
Histon	CB49JD	52.2513	0.118532	3817	118	3935	Y	N	Y
Huntingdon	PE293DF	52.33137	-0.187000	15025	791	15816	Y	Y	Y
Kentford	CB87QD	52.27416	0.492360	2014	92	2106	Y	Y	N
Kimbolton	PE280HJ	52.29729	-0.388230	1217	120	1337	Y	Y	N
Linton	CB16JF	52.09778	0.277723	3275	134	3409	Y	Y	N
Littleport	CB61HT	52.45377	0.302710	3268	113	3381	Y	Y	N
Madingley	CB37QG	52.22351	0.041772	2042	90	2132	Y	Y	N
Manea	PE150HE	52.48961	0.176980	890	53	943	Y	N	N
March	PE158AA	52.55134	0.086930	9150	428	9578	Y	Y	N
Melbourn	SG86DX	52.08466	0.014710	2824	156	2980	Y	N	Y
Mereside	PE262TS	52.49813	-0.126400	687	48	735	Y	Y	N
Newton Wisbech	PE135HR	52.71023	0.115170	1038	51	1089	Y	Y	N
Papworth St Agnes	CB38QU	52.26356	-0.142601	1545	55	1600	Y	N	Y
Parson Drove	PE134JP	52.65613	0.019360	1187	59	1246	Y	N	N
Prickwillow	CB74UN	52.41660	0.344200	279	15	294	Y	N	N
Pymore	CB62TB	52.43143	0.232980	949	22	971	Y	Y	N
Ramsey Hunts	PE261NA	52.44585	-0.112350	4134	236	4370	Y	Y	N
Sawston	CB24HP	52.17524	0.126280	4861	294	5155	Y	Y	Y
Sawtry	PE285TG	52.43865	-0.281420	2615	121	2736	Y	Y	N
Science Park	CB41XT	52.22411	0.137420	4213	317	4530	Y	Y	Y
Six Mile Bottom	CB80UF	52.19073	0.310340	134	9	143	Y	N	N
Soham	CB75AA	52.33003	0.340330	4272	146	4418	Y	Y	N
Somersham	PE283EE	52.38236	-0.001460	3449	180	3629	Y	Y	N
St Ives	PE275BP	52.32735	-0.074370	11434	626	12060	Y	Y	Y
St Neots	PE191AQ	52.22915	-0.269820	14784	651	15435	Y	Y	Y
Steeple Morden	SG80PD	52.07015	-0.124700	1151	35	1186	Y	N	N
Stetchworth	CB89UW	52.19153	0.384340	876	36	912	Y	N	N
Stretham	CB63XN	52.34748	0.220790	1094	23	1117	Y	Y	N
Sutton	CB62QF	52.39217	0.125940	2201	51	2252	Y	Y	N
Swavesey	CB45QY	52.30106	-0.004534	2523	119	2642	Y	Y	Y
Teversham	CB58SP	52.21387	0.167110	2242	49	2291	Y	N	Y
Trumpington	CB22HR	52.17367	0.110348	4678	167	4845	Y	Y	Y
Turves	PE72DP	52.55093	-0.032980	743	48	791	Y	N	N
Warboys	PE282RH	52.40353	-0.083470	2172	114	2286	Y	Y	N
Waterbeach	CB59NJ	52.26558	0.191002	4079	125	4204	Y	Y	Y
West Wratting	CB15LU	52.18581	0.162490	808	28	836	Y	Y	N
Whittlesey	PE71SA	52.55555	-0.126300	6052	274	6326	Y	Y	Y
Willingham	CB45HF	52.31423	0.057902	1604	69	1673	Y	N	Y
Winwick	PE285PR	52.41246	-0.378020	377	51	428	Y	Y	N
Wisbech	PE131JF	52.66420	0.156500	13845	660	14505	Y	Y	Y
Wisbech St Mary	PE134RP	52.65243	0.107480	741	44	785	Y	N	N
Woolley	PE285BJ	52.35624	-0.313680	1701	69	1770	Y	Y	N
Yaxley	PE73NT	52.51698	-0.260620	6288	153	6441	Y	Y	Y

B.2 Cambridgeshire Cabinet Data (Exerpt)

No.	Area	Approx. Postcode	Latitude	Longitude	No.	Area	Approx. Postcode	Latitude	Longitude
1	Abbots Ripton	PE28 5YP	52.41235	-0.21285	665	Kentford	CB8 7QH	52.29060	0.49762
2	Abbots Ripton	PE28 2NX	52.36199	-0.15739	666	Kentford	CB8 7FG	52.28588	0.48806
3	Abbots Ripton	PE28 2FR	52.37191	-0.15086	667	Kentford	IP28 6DE	52.29611	0.58071
4	Abbots Ripton	PE28 2LU	52.39817	-0.18397	668	Kentford	IP28 8FR	52.30696	0.50030
5	Abbots Ripton	PE28 4WX	52.37957	-0.22319	669	Kentford	IP28 8GE	52.30443	0.49849
6	Abbots Ripton	PE28 2LB	52.36472	-0.18672	670	Kentford	IP28 8WG	52.31197	0.50158
7	Abbots Ripton	PE28 2NE	52.40285	-0.15781	671	Kentford	IP28 8WJ	52.30519	0.48618
8	Abbots Ripton	PE28 4WX	52.37957	-0.22319	672	Kentford	CB8 7QF	52.27920	0.49172
9	Abbots Ripton	PE28 2LP	52.40136	-0.20694	673	Kentford	IP28 8LA	52.30308	0.48437
10	Abbots Ripton	PE28 2LR	52.40190	-0.23643	674	Kentford	CB8 7PN	52.27077	0.49203
11	Abbots Ripton	PE28 4JW	52.38953	-0.24613	675	Kentford	CB8 7PN	52.27077	0.49203
12	Arrington	SG8 5QH	52.13026	-0.01754	676	Kimbolton	CB8 8QW	52.24996	0.47660
13	Arrington	SG8 0DP	52.12639	-0.08458	677	Kimbolton	CB8 7PL	52.26386	0.47934
14	Arrington	SG8 5RP	52.09936	-0.02135	678	Kimbolton	IP28 8JW	52.30573	0.49464
15	Arrington	SG8 0AH	52.13323	-0.06012	679	Kimbolton	CB8 8GE	52.24743	0.51903
16	Arrington	SG8 0HL	52.11079	-0.07131	680	Kimbolton	CB8 7FE	52.27263	0.49855
17	Arrington	SG8 0BP	52.14744	-0.03674	681	Kimbolton	IP28 8NE	52.29976	0.49368
18	Arrington	SG8 0BN	52.14126	-0.02867	682	Kimbolton	IP28 8ER	52.30836	0.49249
19	Arrington	SG8 0HB	52.11851	-0.08195	683	Kimbolton	CB8 7QH	52.29060	0.49762
20	Arrington	SG8 5RA	52.14054	-0.00972	684	Kimbolton	CB8 7FG	52.28588	0.48806
21	Arrington	SG8 0HS	52.10201	-0.10276	685	Kimbolton	IP28 6DE	52.29611	0.58071
22	Arrington	SG8 0AQ	52.12725	-0.05488	686	Kimbolton	IP28 8FR	52.30696	0.50030
23	Arrington	SG8 5QQ	52.12056	-0.05249	687	Kimbolton	IP28 8GE	52.30443	0.49849
24	Benwick	PE15 0EX	52.49461	-0.02628	688	Kimbolton	IP28 8WG	52.31197	0.50158
25	Benwick	PE15 0XJ	52.49953	-0.02717	689	Kimbolton	IP28 8WJ	52.30519	0.48618
26	Benwick	PE15 0UH	52.50072	0.00350	690	Kimbolton	CB8 7QF	52.27920	0.49172
27	Benwick	PE15 0UN	52.51839	-0.00092	691	Kimbolton	IP28 8LA	52.30308	0.48437
28	Benwick	PE15 0UB	52.52058	0.11157	692	Kimbolton	CB8 7PN	52.27077	0.49203
29	Benwick	PE15 0UD	52.50970	0.02107	693	Kimbolton	CB8 7PN	52.27077	0.49203
30	Benwick	PE7 2HU	52.51686	-0.06267	694	Linton	CB21 6AB	52.11687	0.23909
31	Benwick	PE15 0UU	52.49690	-0.02446	695	Linton	CB21 4HB	52.12124	0.30398
32	Bottisham	CB25 0FG	52.23837	0.27801	696	Linton	CB21 6AD	52.11745	0.22846
33	Bottisham	CB25 9DN	52.23353	0.26105	697	Linton	CB21 6BT	52.11095	0.25239
34	Bottisham	CB25 9AA	52.22020	0.22408	698	Linton	CB21 4AG	52.09544	0.27274
35	Bottisham	CB25 9BB	52.21898	0.26736	699	Linton	CB21 6AF	52.11446	0.23763
36	Bottisham	CB25 9DL	52.22566	0.25443	700	Linton	CB21 4NX	52.07949	0.27231
37	Bottisham	CB25 9BP	52.22312	0.26252	701	Linton	CB21 4NQ	52.09723	0.28965
38	Bottisham	CB25 9AX	52.22469	0.26227	702	Linton	CB21 4DP	52.13086	0.31747
39	Bottisham	CB25 9EL	52.24320	0.24178	703	Linton	CB21 4EP	52.13308	0.31146
40	Bottisham	CB21 5JY	52.20287	0.25379	704	Linton	CB21 6AG	52.11155	0.23628
41	Buckden	PE19 5AB	52.28707	-0.20814	705	Linton	CB21 4NA	52.09530	0.29457
42	Buckden	PE28 0BP	52.28749	-0.30906	706	Linton	CB21 4QA	52.10115	0.35401
43	Buckden	PE19 5QY	52.29319	-0.24904	707	Linton	CB21 6BE	52.12144	0.23041
44	Buckden	PE19 5GE	52.28203	-0.21287	708	Linton	CB21 4HY	52.09953	0.27661
45	Buckden	PE28 0AY	52.30891	-0.29655	709	Linton	CB21 4UA	52.10347	0.27205
46	Buckden	PE19 5SH	52.29344	-0.25233	710	Linton	CB24 6WZ	52.24487	0.16735
47	Buckden	PE19 5XF	52.29119	-0.25607	711	Linton	CB21 6AL	52.11713	0.22588
48	Buckden	PE19 5BH	52.29133	-0.22300	712	Linton	CB21 4JD	52.10366	0.26839
49	Buckden	PE19 5EY	52.29311	-0.25554	713	Linton	CB21 4NU	52.08122	0.27258
50	Buckden	PE19 5WS	52.28917	-0.24705	714	Linton	CB21 4LE	52.10807	0.29561
51	Buckden	PE19 5UJ	52.30528	-0.23824	715	Linton	CB21 6BP	52.12156	0.24057
52	Buckden	PE28 4NQ	52.32947	-0.25438	716	Linton	CB21 4JQ	52.10143	0.28171
53	Burwell	CB25 0AH	52.26715	0.32375	717	Linton	CB21 6AJ	52.11065	0.22723
54	Burwell	CB25 0BE	52.28772	0.33000	718	Littleport	CB6 1NE	52.45697	0.30753
55	Burwell	CB25 0AX	52.27062	0.33753	719	Littleport	CB6 1EJ	52.50274	0.29578
56	Burwell	CB25 0DX	52.25331	0.30092	720	Littleport	CB6 1HZ	52.46050	0.29520
57	Burwell	CB25 0BY	52.28273	0.32542	721	Littleport	CB6 1GY	52.45004	0.30006
58	Burwell	CB25 0AB	52.27891	0.33246	722	Littleport	CB6 1GZ	52.45677	0.30880
59	Burwell	CB25 0AD	52.28314	0.33058	723	Littleport	CB6 1EE	52.46919	0.32468
60	Burwell	CB25 0BU	52.26698	0.32518	724	Littleport	CB6 1FD	52.45862	0.29402
61	Burwell	CB25 0AY	52.28196	0.32294	725	Littleport	CB6 1RB	52.46390	0.28157
62	Burwell	CB25 0JA	52.26833	0.29693	726	Littleport	CB6 1FE	52.45303	0.31592
63	Burwell	CB25 0JE	52.27652	0.32963	727	Littleport	CB6 1FL	52.45336	0.29379
64	Burwell	CB25 0HD	52.27270	0.32738	728	Littleport	CB6 1EX	52.45591	0.29768
65	Burwell	CB25 0HR	52.27339	0.32888	729	Littleport	CB6 1FG	52.45726	0.29545
66	Burwell	CB25 0AW	52.25555	0.32622	730	Littleport	CB6 1FA	52.45641	0.30543
67	Burwell	CB25 0AZ	52.28142	0.32287	731	Madingley	CB23 7AN	52.21781	-0.00083
68	Burwell	CB25 0JG	52.27715	0.33143	732	Madingley	CB23 7GU	52.20986	0.06360
69	Burwell	CB25 0PA	52.27163	0.33364	733	Madingley	CB23 7RY	52.21012	-0.02442
70	Burwell	CB25 0AA	52.27814	0.32935	734	Madingley	CB23 7PH	52.21425	0.04765
71	Burwell	CB25 0JE	52.27652	0.32963	735	Madingley	CB23 7QR	52.21481	0.01075
72	Bythorn	PE28 0PN	52.35584	-0.40736	736	Madingley	CB23 7AH	52.20506	0.00337

73	Bythorn	PE28 0PB	52.34773	-0.40073
74	Bythorn	PE28 0QP	52.37199	-0.44872
75	Bythorn	PE28 0PJ	52.35658	-0.43036
76	Bythorn	PE28 0RD	52.36505	-0.46765
77	Bythorn	PE28 0QN	52.36963	-0.44927
78	Bythorn	PE28 0RQ	52.34305	-0.45305
79	Bythorn	PE28 0QA	52.38004	-0.41124
80	Bythorn	PE28 0RA	52.37722	-0.47169
81	Bythorn	PE28 0PW	52.36130	-0.40906
82	Bythorn	PE28 5BA	52.36040	-0.38119
83	Bythorn	PE28 0PW	52.36130	-0.40906
84	Bythorn	PE28 0RF	52.36614	-0.46946
85	Cambridge	CB4 1AY	52.21849	0.13327
86	Cambridge	CB4 1XD	52.21902	0.13071
87	Cambridge	CB4 1AE	52.21604	0.12684
88	Cambridge	CB4 2BZ	52.22183	0.11955
89	Cambridge	CB1 2JY	52.19472	0.13240
90	Cambridge	CB1 2JB	52.19519	0.13156
91	Cambridge	CB1 2ED	52.19934	0.13480
92	Cambridge	CB1 2EU	52.19878	0.12827
93	Cambridge	CB4 3HA	52.22063	0.11333
94	Cambridge	CB3 0AT	52.21395	0.11113
95	Cambridge	CB4 3DA	52.21484	0.11490
96	Cambridge	CB4 3HW	52.22133	0.11028
97	Cambridge	CB2 1AX	52.20211	0.12428
98	Cambridge	CB1 1AH	52.20743	0.12311
99	Cambridge	CB3 0HN	52.21880	0.10424
100	Cambridge	CB3 0AZ	52.21240	0.10480
101	Cambridge	CB2 1TP	52.20778	0.11783
102	Cambridge	CB4 3AG	52.21316	0.11659
103	Cambridge	CB3 0EH	52.20904	0.10316
104	Cambridge	CB2 1JF	52.19377	0.12874
105	Cambridge	CB3 9AP	52.20042	0.10397
106	Cambridge	CB3 9AT	52.19889	0.10453
107	Cambridge	CB3 9AH	52.20224	0.11190
108	Cambridge	CB3 9BT	52.19717	0.10857
109	Cambridge	CB2 7TS	52.19111	0.12285
110	Cambridge	CB2 1EP	52.19794	0.12509
111	Cambridge	CB1 2DN	52.19679	0.13570
112	Cambridge	CB4 1DZ	52.21673	0.13979
113	Cambridge	CB4 1BU	52.21448	0.13453
114	Cambridge	CB4 1AT	52.21675	0.13181
115	Cambridge	CB4 1HD	52.21358	0.12837
116	Cambridge	CB4 1AB	52.21499	0.12738
117	Cambridge	CB4 3AR	52.21384	0.12258
118	Cambridge	CB1 2AG	52.19731	0.13865
119	Cambridge	CB1 2AB	52.20154	0.13379
120	Cambridge	CB1 1BL	52.20489	0.13455
121	Cambridge	CB1 1AZ	52.20515	0.13092
122	Cambridge	CB1 2QZ	52.20858	0.14235
123	Cambridge	CB1 1BU	52.20740	0.13775
124	Cambridge	CB1 1HN	52.20783	0.13422
125	Cambridge	CB1 1HA	52.20736	0.12942
126	Cambridge	CB1 1EH	52.20443	0.12851
127	Cambridge	CB4 2EG	52.22483	0.12647
128	Cambridge	CB4 3GY	52.21890	0.11054
129	Cambridge	CB4 2EH	52.22558	0.12338
130	Cambridge	CB1 1AJ	52.20549	0.13209
131	Cambridge	CB4 1DN	52.21566	0.14032
132	Cambridge	CB2 1FR	52.20913	0.11858
133	Cambridge	CB1 2AA	52.19242	0.13450
134	Cambridge	CB2 1UB	52.20852	0.11952
135	Cambridge	CB1 2DY	52.19661	0.13367
136	Cambridge	CB2 1AG	52.19991	0.12180
137	Cambridge	CB2 1DS	52.20348	0.11656
138	Cambridge	CB2 1SP	52.20484	0.11789
139	Cambridge	CB4 2LH	52.22817	0.13120
140	Cambridge	CB1 2LY	52.20637	0.13869
141	Cambridge	CB1 1PE	52.20672	0.12122
142	Cambridge	CB1 1PW	52.20703	0.12112
143	Cambridge	CB3 0DW	52.21440	0.09102
144	Cambridge	CB1 2NS	52.20387	0.14412
145	Cambridge	CB1 3ER	52.20592	0.14540
146	Cambridge	CB4 2JL	52.22903	0.12205
147	Cambridge	CB4 2HD	52.22622	0.11459
148	Cambridge	CB4 3BX	52.21518	0.11385
149	Cambridge	CB4 3PX	52.21758	0.10694

737	Madingley	CB23 7UE	52.20938	-0.02709
738	Madingley	CB23 8AR	52.22382	0.00099
739	Madingley	CB23 8AZ	52.21946	-0.01852
740	Manea	PE15 0BF	52.48536	0.17693
741	Manea	PE15 0FA	52.48273	0.17178
742	Manea	PE15 0FP	52.49169	0.17650
743	Manea	PE15 0DU	52.51866	0.15038
744	Manea	PE15 0PE	52.50158	0.11631
745	Manea	PE15 0DX	52.51407	0.14509
746	Manea	PE15 0HH	52.51019	0.18172
747	Manea	PE15 0DX	52.51407	0.14509
748	Manea	PE15 0DZ	52.48488	0.11403
749	Manea	PE15 0JR	52.49316	0.15639
750	Manea	PE15 0HN	52.51127	0.20418
751	March	PE15 0BF	52.48536	0.17693
752	March	PE15 0FA	52.48273	0.17178
753	March	PE15 0FP	52.49169	0.17650
754	March	PE15 0DU	52.51866	0.15038
755	March	PE15 0PE	52.50158	0.11631
756	March	PE15 0DX	52.51407	0.14509
757	March	PE15 0HH	52.51019	0.18172
758	March	PE15 0DX	52.51407	0.14509
759	March	PE15 0DZ	52.48488	0.11403
760	March	PE15 0JR	52.49316	0.15639
761	March	PE15 0HN	52.51127	0.20418
762	Melbourn	SG8 6JR	52.09066	0.00882
763	Melbourn	SG8 6BN	52.08189	0.01589
764	Melbourn	SG8 6EJ	52.08531	0.01766
765	Melbourn	SG8 6GB	52.11370	0.03092
766	Melbourn	SG8 6FP	52.10382	0.01470
767	Melbourn	SG8 6AR	52.07970	0.01364
768	Melbourn	SG8 6BD	52.07960	0.01695
769	Melbourn	SG8 6DN	52.07607	0.01590
770	Melbourn	SG8 6BY	52.07859	0.02177
771	Melbourn	SG8 6DT	52.08963	0.01581
772	Melbourn	SG8 6EE	52.08810	0.02567
773	Melbourn	SG8 5RL	52.10225	-0.01043
774	Melbourn	SG8 6JP	52.08637	0.01069
775	Melbourn	SG8 6AE	52.08384	0.01275
776	Melbourn	SG8 6AB	52.08318	0.01516
777	Mereside	PE26 2SQ	52.51264	-0.14438
778	Mereside	PE26 2UA	52.48372	-0.10750
779	Mereside	PE26 2SP	52.48059	-0.15231
780	Mereside	PE26 2TJ	52.49514	-0.14698
781	Mereside	PE26 2TT	52.49022	-0.11548
782	Mereside	PE26 2TU	52.48896	-0.12365
783	Newton Wisbeach	PE14 9QN	52.53717	0.22398
784	Newton Wisbeach	PE14 9LF	52.54882	0.20107
785	Newton Wisbeach	PE14 9JG	52.56105	0.22728
786	Newton Wisbeach	PE14 9LU	52.57243	0.17131
787	Newton Wisbeach	PE14 9LN	52.56455	0.19865
788	Newton Wisbeach	PE14 9JD	52.55983	0.21653
789	Newton Wisbeach	PE14 9JE	52.55457	0.21476
790	Newton Wisbeach	PE14 9LT	52.57380	0.17657
791	Newton Wisbeach	PE14 9LE	52.56144	0.18483
792	Papworth St Agnes	CB23 3GT	52.25396	-0.11586
793	Papworth St Agnes	PE28 9NF	52.28138	-0.11153
794	Papworth St Agnes	CB23 3AE	52.24359	-0.11532
795	Papworth St Agnes	CB23 3HJ	52.24922	-0.12116
796	Papworth St Agnes	CB23 3GJ	52.25217	-0.12339
797	Papworth St Agnes	PE19 6PJ	52.26106	-0.16696
798	Papworth St Agnes	CB23 3LE	52.24462	-0.11300
799	Papworth St Agnes	PE28 9JA	52.28482	-0.09615
800	Papworth St Agnes	PE28 9NJ	52.27691	-0.11118
801	Papworth St Agnes	CB23 3QU	52.26363	-0.14281
802	Papworth St Agnes	PE28 9PA	52.28357	-0.14231
803	Papworth St Agnes	PE29 2LJ	52.29618	-0.15448
804	Papworth St Agnes	PE19 6PH	52.26158	-0.16662
805	Parson Drove	PE13 4HQ	52.63146	0.02547
806	Parson Drove	PE13 4JE	52.66956	0.03464
807	Parson Drove	PE12 0QN	52.66538	-0.01273
808	Parson Drove	PE13 4HA	52.65555	0.02413
809	Parson Drove	PE13 4LD	52.66180	0.03999
810	Parson Drove	PE12 0LJ	52.69624	0.00393
811	Parson Drove	PE13 4JT	52.64642	0.00596
812	Parson Drove	PE13 4LF	52.66095	0.05046
813	Parson Drove	PE12 0RA	52.66370	-0.02147

B.3 Average Download Speeds

Historic average download speeds:

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
Average Download Speed (Mbit/s)	4.10	5.20	6.80	9.00	17.80	22.80	28.90	36.20	46.20

Projected average download speeds at 1.13% growth:

Year	2017	2018	2019	2020	2021	2022	2023	2024	2025
Average Download Speed (Mbit/s)	46.20	52.21	58.99	66.66	75.33	85.12	96.19	108.69	122.82

Year	2026	2027	2028	2029	2030	2031	2032
Average Download Speed (Mbit/s)	138.79	156.83	177.22	200.25	226.29	255.71	288.95